The Beckman Institute for Advanced Science and Technology

Evidence for Structural Alignment
During Similarity Judgments

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Cognitive Science
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Similarity plays a central role in cognitive theories. Much research has been devoted to understanding what makes a pair of objects similar. This research has demonstrated that the similarity of a pair increases with its commonalities and decreases with its differences. These common and distinctive elements can take the form of parts of objects, relations between parts of properties of whole objects. Previous work has been unable to reconcile this variety of information within a single framework. We suggest that structural alignment, like that proposed to mediate analogical reasoning, provides a sufficiently powerful process for determining the commonalities and differences of complex representations. The main prediction of this approach is that similarity comparisons focus subjects on the global commonalities of a pair. A second prediction is that salient local similarities temper the preference for a global alignment. We test these hypotheses in four experiments using the one-shot mapping technique, which places local and global similarities in opposition. The results support the predictions of the structural alignment view, and highlight the importance of the binding between relations and their arguments for similarity.

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Evidence for Structural Alignment During Similarity Judgments

Similarity plays a central role in cognitive theories. Much research has been devoted to understanding what makes a pair of objects similar. This research has demonstrated that the similarity of a pair increases with its commonalities and decreases with its differences. These common and distinctive elements can take the form of parts of objects, relations between parts or properties of whole objects. Previous work has been unable to reconcile this variety of information within a single framework. We suggest that structural alignment, like that proposed to mediate analogical reasoning, provides a sufficiently powerful process for determining the commonalities and differences of complex representations. The main prediction of this approach is that similarity comparisons focus subjects on the global commonalities of a pair. A second prediction is that salient local similarities temper the preference for a global alignment. We test these hypotheses in four experiments using the one-shot mapping technique, which places local and global similarities in opposition. The results support the predictions of the structural alignment view, and highlight the importance of the binding between relations and their arguments for similarity.

Introduction

The concept of similarity has played an important role in theories of cognitive processes. For example, categorization models (i.e., Rosch, 1975; Medin and Schaffer, 1978; Nosofsky, 1986) assume that new exemplars are categorized based on their similarity to some prototype, abstraction or previous exemplar. Theories of problem solving (Ross, 1987, 1989; Holyoak and Koh, 1987; Novick, 1988) propose that a new problem is solved by using previous similar problems as examples. Norm theory (Kahneman and Miller, 1986) presupposes that new situations are categorized based on prototypical instances constructed from prior similar episodes. Theories of transfer (Thorndike and Woodworth, 1901, Singley and Anderson, 1989) propose that new skills will be easier to learn to the extent that they are similar to things previously learned.

Because of its wide application in theories of cognition, similarity itself has also become the subject of psychological inquiry. Two compelling views of similarity have arisen from this research: one that emphasizes the role of local features in similarity (James, 1892; Tversky, 1977; Sattath and Tversky, 1977), and another that demonstrates that feelings of similarity are sensitive global stimulus properties (Wertheimer, 1923; Goldmeier, 1937; Palmer, 1977). It has been difficult to include both types of information in a single process model that determines the commonalities and differences of a pair during a comparison. In this paper, we present an approach to similarity that views the comparison of objects as an alignment and evaluation procedure akin to the one proposed to mediate analogical reasoning and allows local and global information to coexist.

Feature Matching models of Similarity

Tversky's (1977) influential contrast model is a formalization of the fundamental insight that both commonalities and differences affect the calculation of similarity. This elegant model has provided the basis for inquiries into the nature of psychological similarity, and has been incorporated into models of other cognitive processes. The contrast model rests on three primary assumptions: matching, monotonicity and independence. The *matching* assumption formalizes the intuition that similarity is a function of both the features shared by two items (*common features*) and the features possessed by one object, but not the other (*distinctive features*). The *monotonicity* assumption adds the restriction that common features only increase similarity, and distinctive features only decrease similarity. Finally, the *independence* assumption states that the joint effect of any two of the sets of common and distinctive features (the *components* of similarity) on similarity does not alter the effect of the third set on similarity.[1]

Given these assumptions, the similarity of two objects a and b ($s(a,b)$), represented as feature sets A and B respectively, may be written as:

$$s(a,b) = \theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A), \tag{1}$$

where $A \cap B$, $A - B$ and $B - A$ are the components of similarity. The functions $F(X)$ increase monotonically with the size of their argument X and serve to establish the salience weights of the features in the set. An additional assumption of feature independence is sometimes added to allow the functions to be a weighted sum of the features in each component, but this assumption is not an inherent part of the contrast model. Finally, the constants θ, α, and β fix the relative weights of the common and distinctive features for a given judgment.

The work spawned by this approach has often centered on the role of local features in the calculation of similarity. For example, Tversky (1977) tested the predictions of the contrast model on stimuli like schematic faces that can be described locally by the shapes of the eyes, nose and mouth. Similarly, Sattath and Tversky (1977) presented subjects with printed letters, and found that subjects' similarity judgments were based on local properties like the length and curvature of line segments.

Global Properties and Similarity

A second approach to the study of similarity has focused on global perceptual properties of objects. In early studies, the Gestalt psychologists demonstrated that global properties like overall shape and goodness of form are important to the processing of similarity (Wertheimer, 1923; Goldmeier, 1937). Palmer (1977) has suggested that these global perceptual properties can be characterized as configural *relations* between structural units (like line segments). These relational groups may be hierarchically organized by additional relations. To support this conjecture, Palmer asked subjects to 'parse' a set of configurations constructed from line segments

[1] In specifying the axioms making up the contrast model, Tversky (1977, Appendix) adds *solvability* and *invariance* to the matching, monotonicity and independence assumptions. Solvability states that a set of features can be found to represent each object, and that, once the feature sets for a pair are determined, the similarity can be computed. Invariance claims that the magnitude of the impact of a set of features making up an entire component will be the same no matter which component they make up (commonalities or a set of differences).

into their 'natural parts', and found that they often divided figures into the predicted types of relational groupings. He obtained similar results with other methodologies.

Another line of research directed at the same problem examined global perceptual properties in the form of emergent features (Pomerantz, Sager and Stoever, 1977; Lockhead and King, 1977; Treisman and Paterson, 1984). In one study, Pomerantz, Sager and Stoever (1977) found that subjects required less time to differentiate the patterns ((and () than they did to differentiate the patterns (and), because the first pair and not the second gives rise to emergent features.

Relations in perceptual representations form the basis of Biederman's (1987) recognition-by-components theory of object perception. According to this theory, object representations are composed of primitive visual elements (called *geons*) and the relations between them. In order to recognize an object, subjects must identify both the geons that make up the object and the spatial relations between these geons. To support this hypothesis, Biederman presented subjects with line drawings of common objects from which line segments had been removed. Objects in the degraded drawings were easier to identify if the junctions between line segments were preserved (thereby preserving information about relations between geons), than if these junctions were erased.

Research has also focused on the importance of relations in conceptual stimuli. Goldstone, Medin and Gentner (1991) found that subjects can be differentially sensitive to perceptual descriptions of objects (*attributes*) and relations between objects. Their results indicate that increasing the relational similarity of two scenes has a greater impact on their perceived similarity if the commonalities of the scenes are primarily relational than if the commonalities are primarily attributional. Similarly, increasing the attributional similarity of two scenes has a greater impact on their perceived similarity if the pair contains primarily object similarities. To account for these data, Goldstone et al. proposed the MAX model, which assumes that matching attributes and matching relations form two 'pools.' During a similarity judgment, the elements in the larger pool are given more weight than the elements in the smaller pool. The importance of relations in the processing of conceptual stimuli has also been demonstrated by Gentner and her colleagues (Rattermann and Gentner, 1987; Schumacher and Gentner, 1987) who found that stimuli containing only relational commonalities were often considered to be more similar than stimuli containing only local object commonalities.

Combining these approaches

Both local and global properties appear to play a role in determining similarity. Since the contrast model is neutral with respect to the content of mental representations, an obvious way to combine these types of information would be to include features that encode local and global information in the same representation. Indeed, Tversky (1977) allows that the features representing a pair of objects could denote "appearance, function, relation to other objects, and any other property of the object that can be deduced from our general knowledge of the world" (Tversky, 1977, p. 329). In principle this suggestion seems straightforward, but a deeper analysis reveals that the process of finding the commonalities and differences of a pair becomes more complex when local and global information coexists.

When the local and global features are consistent, the commonalities of a pair can be determined simply. For example, in Figure 1a, the circle is above the square in both configurations. Using the feature lists below each configuration, the local features of the individual objects as

well as the global feature 'above' can be matched, leading to a high rated similarity.

In contrast, the pair in Figure 1b is constructed from the same objects used in Figure 1a, but the pair is clearly no longer identical. Intuitively, when determining the commonalities and differences of this pair, the circle and square could be placed in correspondence because they are both 'on top.' Then, the figures would be similar in their configuration of shapes, but different in the shapes on the top and bottom. In contrast, the identical circles could be placed in correspondence because of their commonalities in shape and shading. In this case the figures would be similar because they contain the same shapes, but different because these shapes no longer occupy the same relative positions. Either way of matching these figures is plausible. However, using a simple featural representation, like that presented below the configurations, there is no explicit connection between the global feature 'above' and the local object features. Because the global and local features are not connected, there is no principled way for object features to be placed in correspondence on the basis of the configural similarity.

The particular problem exposed by this example (which we will refer to as *the binding problem*) is that a collection of features does not provide information about the connection between objects, their descriptions and more global properties. The role of bindings in similarity comparisons has been the subject of empirical study. Goldstone (submitted, Goldstone and Medin, in press) presented subjects with pairs of pairs of schematic butterflies. He found that attribute matches bound to corresponding objects (i.e., those that shared many attributes) received greater weight than attribute matches bound to non-corresponding objects (i.e., those that shared few attribute matches).

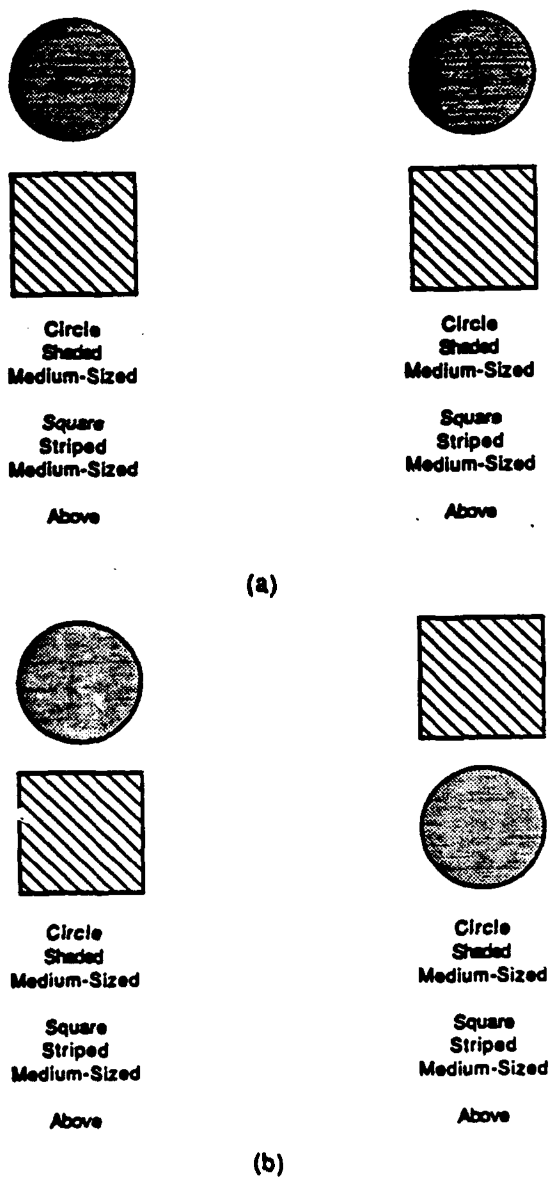
Solution of the binding problem requires that connections between objects, object descriptions and relations be encoded explicitly. A simple extension to featural representations that addresses this issue adds configural features, like 'abovecirclesquare,' to representations (Foss and Harwood, 1975). The purpose of these features is to encode the links between local and global properties. However, this solution leads to a proliferation of configural features, because a new feature must be created for each combination of local and global properties.

The binding problem can be handled without an explosion of new features using propositional representations. Global stimulus properties can be represented as *relations* between other elements. A relation is a proposition that connects two or more *arguments* that may be objects, object descriptions (called *attributes*), other relations or other propositions. In this type of representation, the binding problem is solved by having predicates take the elements they are bound to as arguments (e.g., above (circle, square)).

One problem with propositional representations is that set operations cannot be used to find a pair's commonalities and differences as in featural models. Rather, the comparison of propositional representations requires a complex alignment pr·cess sensitive to the bindings between relations and their arguments. Fortunately, this theme has been taken up by studies of analogical mapping, which have traditionally been concerned with the alignment of complex representations. We turn to this work in an effort to extend it ordinary similarity comparisons.

Figure 1

Stimuli illustrating the binding problem. The first pair (a) is identical. The second pair (b) is made up of the same two objects, but is no longer identical.



Analogical reasoning and binding

Finding the similarity of two potential analogs has been widely studied (see Kedar-Cabelli, 1985 and Hall, 1989 for general reviews of the field). The general approach to analogical reasoning taken by many theorists is to assume that analogies involve connected relational similarities (Bakker and Halford, 1988; Gentner, 1983, 1989; Greiner, 1988; Holyoak and Thagard, 1989; Indurkhya, 1986 and Keane, 1990; Winston, 1982). For example, Gentner's (1983, 1989) structure-mapping theory (SMT) can be applied to the analogy between the solar system and an atom presented in Figure 2. The individual objects in the two descriptions are quite dissimilar, but both the solar system and hydrogen atom possess similar relations between the objects. During analogical mapping, SMT predicts that the sun and the nucleus will be placed in correspondence, as will the planet and the electron, because the planet revolves around the sun, while the electron revolves around the nucleus. Furthermore, SMT assumes that mappings of systems of relations are preferred to mappings of isolated relations. Thus, the fact that the planet is cooler than the sun is not nearly as important as the fact that the planet revolves around the sun, because the second fact, and not the first, is embedded in a deep causal relational structure common to both domains.

A number of studies have examined the role of bindings in analogical reasoning. In one experiment, Gentner and Toupin (1986) demonstrated that inconsistent bindings hinder analogical alignment. In their study, children made fewer errors matching story pairs in which similar characters played similar roles in a similar plot than story pairs in which similar characters played different roles in a similar plot. Gentner and Toupin referred to situations where local and global matches give rise to different object correspondences as *cross-mappings.* In another study, Gentner and Clement (1988) found that adult subjects were more likely to make analogical inferences when the inferred information was connected to a systematic relational match than when the information was not connected to other relational matches. Finally, Wharton, Holyoak, Downing, Lange and Wickens (1991) observed a higher level of retrieval for sentences when the local and global similarities were bound consistently than when they were cross-mapped. All of these studies suggest that binding information is included in mental representations.

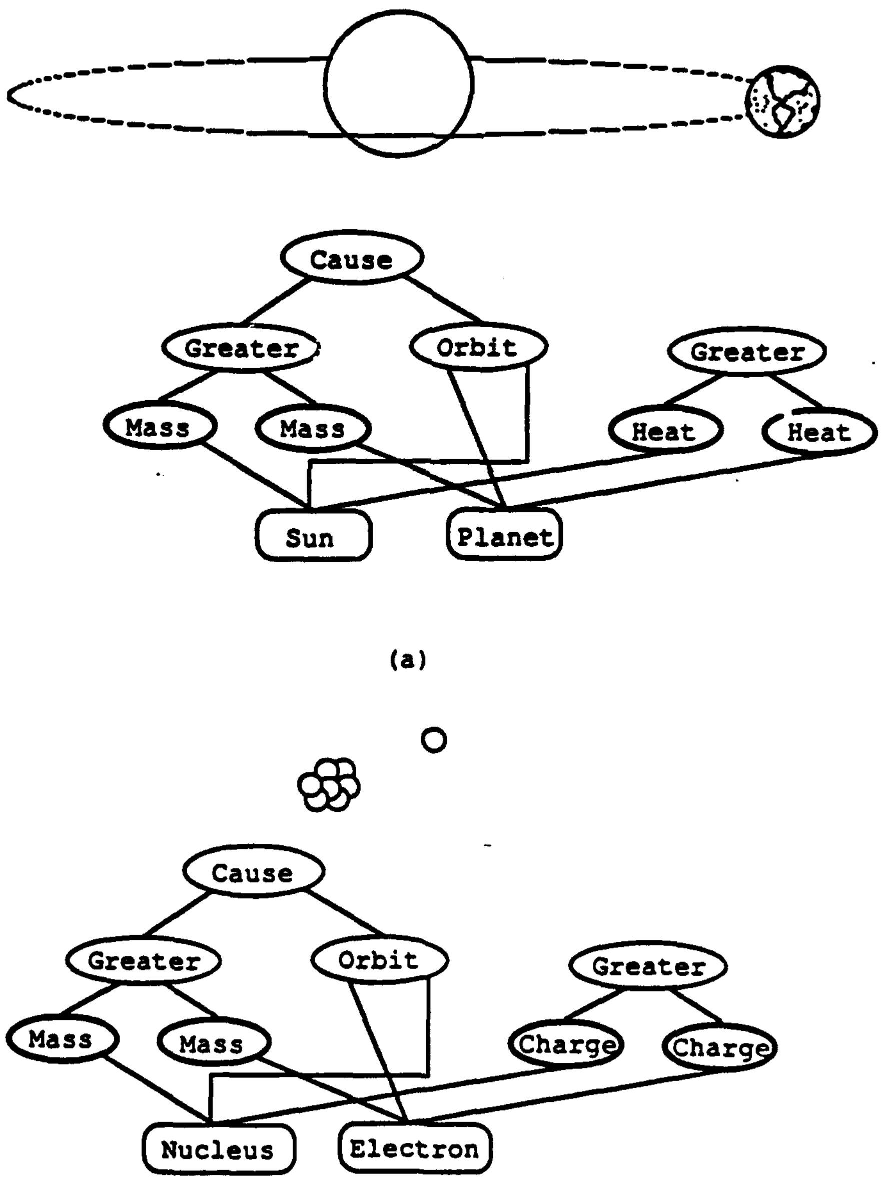
It is a natural extension of an analogical alignment process to include ordinary similarity comparisons. Gentner (1983, 1987, 1989) refers to comparisons that preserve both object similarities and relational similarities as *literal similarity comparisons.* Other alignment models have also been applied to the study of similarity, including Goldstone and Medin's (in press) SIAM. A general outline of the structural alignment view of similarity follows (we defer a more detailed exposition of processing assumptions until after the first experiment).

Structural alignment and similarity

We assume that objects, and the scenes in which they participate, are represented by attributes and relations. In addition, the bindings between propositions and their arguments are represented explicitly. In a propositional representation, attributes can be defined as predicates taking a single argument, while relations can be defined as predicates taking more than one argument, thereby linking two or more objects, attributes or relations.

Figure 2

Analogy between the solar system and the Rutherford atom.



(b)

The commonalities and differences of a pair of representations are determined via a structural alignment process. According to Gentner (1983, 1989), the match between two structured representations must be *structurally consistent*: that is, it must conform to the *one-to-one-mapping* and *connectivity* constraints. One-to-one-mapping means that, for any given match between representations, each element in one representation will map to at most one element in the other representation. Connectivity mandates that if a match is made between predicates, the arguments of those predicates must match as well.

In many cases, more than one structurally consistent match between two representations is possible. However, only a single interpretation will be used as the basis for finding the commonalities and differences when determining the similarity of a pair. The preferred match is generally the one that is most *systematic*. Systematicity requires that deeply connected relational structures be preferred to matches that preserve only scattered, unconnected relational structures. Other factors determining the preferred match are the salience of object similarities, the factual correctness of any inferences arising from the match[2] and the relevance of the match to the current task.

According to the structural-alignment view, similarity comparisons should make use of relational commonalities of a pair. For example, suppose the task were to compare assertions about two different planets:

cause (greater (mass(Sun), mass(Jupiter)), **revolve**(Jupiter,Sun)) (2)

and

cause (greater (mass(Sun), mass(Mars)), **revolve**(Mars,Sun)) (3)

This pair is literally similar because it contains both relational commonalities and object similarities. Thus, Jupiter corresponds to Mars both because, as planets, they share many physical similarities, and because they play a common role in the matching relational structure. In this pair object and relational commonalities are correlated, so the impact of the two types of similarity on this comparison cannot be separated.

However, object and relational similarity can be deconfounded by designing comparisons in which one of the objects is cross-mapped (i.e., the object appears in both relational structures, but plays a different role in each (Gentner and Toupin, 1986)). For example, if (2) is compared with:

cause (greater (mass(Jupiter), mass(Io)), **revolve**(Io,Jupiter)) (4)

then Jupiter is cross-mapped. This cross-mapping can be resolved in two ways: either by structural alignment, in which case Jupiter and Io should be placed in correspondence, or by object-matching, in which case Jupiter will be placed in correspondence with Jupiter.

The central claim of this research is that performing a similarity comparison promotes structural alignment. This means that, all else being equal, the likelihood of a structural alignment between two stimuli is greater after a similarity comparison than before. This prediction can

[2]Structure-mapping theory allows *candidate inferences* to be proposed based on the structure of the matching information.

be tested empirically by presenting subjects with pairs of scenes containing cross-mappings, and asking them first to rate the similarity of the scenes, and then to perform a *one-shot mapping*. In one-shot mapping, an Experimenter points to the cross-mapped object in one scene and asks the subject to select the object in the other scene that goes with that object. The neutral phrase 'goes with' is used so that the subject is not biased to select either the object or relational choice. If subjects arrive at the relational match between scenes when performing a similarity comparison, they should align the objects based on the matching relations in the subsequent one-shot mapping. This prediction contrasts with our expectation for subjects' one-shot mappings if no similarity comparison is performed. In this case, subjects need not consider the overall similarity of the scenes, and we expect them to map on the basis of the local object similarities.

For example, Figure 3 presents a sample stimulus from the first experiment. Notice the women in these scenes are cross-mapped. Even though they are perceptually similar, the woman in Figure 3a is receiving food from the man, while the woman in Figure 3b is giving food to the squirrel. We would expect subjects who perform a simple one-shot mapping to align the two women based on their perceptual similarity. However, subjects who first rate the similarity of the pair should place the woman in Figure 3a in correspondence with the squirrel in Figure 3b because they play a common role in the matching relational structure.

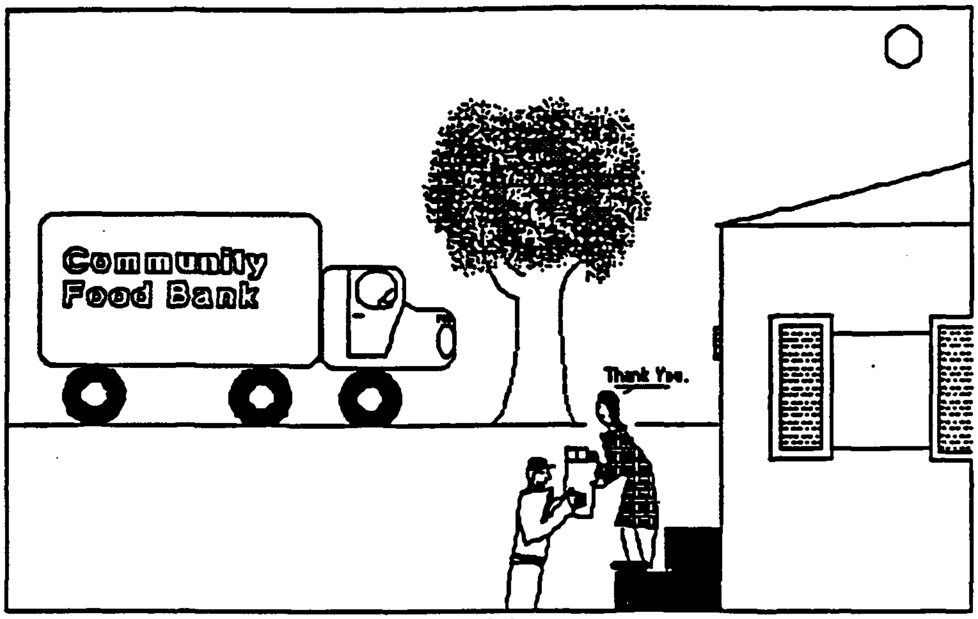
Finding that subjects make more relational mappings following a similarity rating than without one would suggest that the similarity comparison process involves structural alignment. However, a convergent task is needed to assess subjects' ability to make relational mappings for the stimulus pairs. For this purpose, a third condition was included in which subjects were asked to make three object mappings for each pair of scenes. This more comprehensive mapping task, which requires that subjects consider several simultaneous object correspondences, should force them to align the objects based on the matching relational structure. In the current example, while the women in Figures 3a and 3b can be matched on the basis of perceptual similarities, there is no perceptual match in Figure 3b for the man in Figure 3a. The only plausible match for this object is the woman in Figure 3b who is also giving away food. However, we assume that subjects have a bias against mapping an object in one scene with more than one object in the other scene. Hence, they should rarely place *both* the woman and man in Figure 3a in correspondence with the woman in Figure 3b. These predictions will be tested in Experiment 1.

Experiment 1

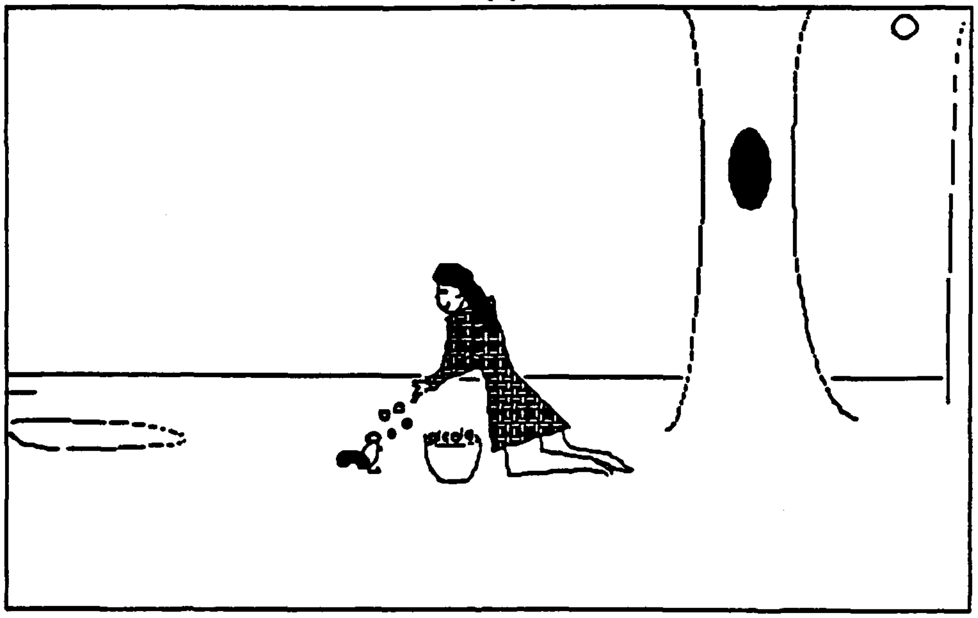
Experiment 1 uses the one-shot mapping technique to examine the plausibility of structural alignment as the mechanism underlying similarity comparisons. For this purpose, eight pairs of causal scenes were drawn. Each pair contained a cross-mapped object. A sample stimulus pair is presented in Figure 3. With this stimulus set, subjects were run in one of the three experimental conditions described above. Subjects in the *1map* condition performed a one-shot mapping on each scene, and later rated the similarity of all of the scenes. Subjects in the *Sim->1map* condition first rated the similarity of the scenes and then performed the one-shot mapping. Finally, subjects in the *3map* condition performed three mappings for each pair of scenes, and later rated their similarity.

Figure 3

Sample pair of causal scenes containing a cross-mapping. The woman in the top scene is receiving food, while the woman in the bottom scene is giving food away.



(a)



(b)

Let us review the predictions for this task. Subjects in the Sim->1map condition should map on the basis of the matching relational structure. This result is predicted on the grounds that carrying out a similarity comparison will cause subjects to align the scene representations, thereby increasing their sensitivity to the common relations. In contrast, subjects in the 1map condition should map on the basis of local object similarities, because simple one-shot mapping does not require a global comparison of the scenes. Finally, subjects in the 3map condition should make many relational responses, because, as described above, the common relations provide a natural basis for multiple consistent mappings. We make no ordinal predictions about the level of relational responding in the Sim->1map condition relative to the 3map condition. We simply expect both conditions to exhibit a higher level of relational responding than the 1map condition.

In addition to the 3map condition, one other control is needed. Subjects in the Sim->1map condition are exposed to the pictures prior to the mapping task, while subjects in the 1map and 3map conditions are not. Thus, if subjects in the Sim->1map condition make more relational responses than subjects in the 1map condition, this difference could be explained by their greater degree of familiarity with the stimuli. To control for this possibility, a *familiarity control* condition is needed. Subjects in this condition are shown all of the pictures individually for five seconds—roughly the amount of time subjects see the pictures when rating their similarity—and are told to study them for a later memory test. Following the study stage, they perform the one-shot mapping task.[3] Subjects in this condition should make fewer relational responses than subjects in the Sim->1map condition.

Method

Subjects. Subjects were 48 undergraduates (12/condition) at the University of Illinois who received $4.00 or course credit in introductory psychology classes for their participation.

Design. Subjects were randomly assigned to one of the three between-subject Mapping conditions or the familiarity control. Four random orders of stimulus presentation were used in each condition. The performance of subjects in the Familiarity Control condition will be compared only to the performance of subjects in the Sim->1map condition.

Stimuli. The stimuli were eight pairs of pictures portraying causal scenes (like the pair in Figure 3). Each pair of scenes contained a cross-mapping. In the context of this experiment, a cross-mapping was operationalized as a pair of perceptually similar objects that played different roles in the matching relational structure of the two scenes. In half of the pairs, the perceptually similar objects occupied roughly the same spatial position in both scenes (as with the two women in Figure 3). In the other half, the objects playing the same role occupied the same spatial position in both scenes. Further, in half of the scenes, the event path moved from left to right (e.g., the giver was on the left and the receiver was on the right) and in the other half the event path moved from right to left. Finally, in half of the scenes the cross-mapped objects were shown in the same left-right orientation and in half of the scenes the objects were flipped horizontally to face in the opposite direction.[4] A summary of the stimulus set is presented in Table 1.

[3] This condition is not designed to test subjects' spontaneous relational mapping ability. Hence, the pictures were presented individually for study.

[4] Although we were able to control these factors somewhat, they were not fully counterbalanced. However, a careful analysis of presentation factors is carried out in Experiment 4.

Table 1
Summary of Causal Stimuli used in Experiment 1

Stimulus	Relation	Relation in Same Direction	Number of Objects	Cross-Mapped Object in Same Orientation	Number of Cross-Mapped Objects	Cross-Mapped Object	Object for Multiple Mapping	
1	Reaching	No	4	Yes	1	Cookie Jar	Person	Chair
2	Repair	Yes	3	No	1	Robot Arm	Wrench	Car
3	Towing	No	3	No	1	Car	Truck	Hook
4	Pitching	No	4	No	1	Pitcher	Batter	Ball
5	Giving	Yes	4	Yes	1	Woman	Man	Bag of Food
6	Execution	Yes	3	No	1	Pirate	Sharks	Rebel
7	Break-In	No	4	Yes	1	Box	Bandit	Knife
8	Eclipse	Yes	3	Yes	2	Earth	Moon	Sun

Procedure. Subjects were run one at a time. They were seated at a table with an experimenter seated beside them. Subjects participated in only one experimental condition. The experimenter had no knowledge of the hypothesis being tested.

Subjects in the one-shot mapping (1map) condition were shown each of the base/target pairs in turn. The experimenter pointed to the cross-mapped object and asked the subject to point to the object in the other picture that went with it. The subject's response was recorded and the next pair of pictures was presented. After completing the mapping task, subjects rated the similarity of each pair on a scale from 1 to 9. Ratings were made orally.

Subjects in the three-mapping (3map) condition were also shown each of the base/target pairs. Before the first trial, subjects were told that they would be making three object mappings. Then, the experimenter pointed (one at a time) to three of the objects making up the central relational structure of one scene, and asked the subject to point to the object in the other scene that went with each object. The cross-mapped object was always tested first so that subjects' first responses in the 3map condition would be comparable to subjects' first responses in the other three conditions. After completing the mapping task, these subjects were also asked to rate the similarity of all of the pairs of pictures.

Subjects in the similarity-first task (Sim->1map) were given a pair of scenes and told to rate their similarity on a scale from 1 to 9. After the subject completed the rating for a pair the experimenter pointed to the cross-mapped object and asked the subject to point to the object in the other picture that went with it. The responses were recorded and the next pair was presented.

In the familiarity control condition, subjects were shown the set of pictures one at a time and told to study them carefully for a later memory test. Subjects saw each picture for five seconds, roughly the amount of time subjects in the Sim->1map condition saw the pictures while making similarity comparisons. After examining the entire set of pictures, subjects in the control condition performed the one-shot mapping task.

Results and Discussion

Comparison and Mapping. For each pair, subjects made an *object mapping* if they responded on the basis of perceptual similarity (e.g., matching the two women), a *relational mapping* if they responded on the basis of the common relational structure (e.g., matching the woman with the squirrel) or a *spurious mapping* if any other choice was made (e.g., matching the woman to the tree). Almost all of the responses were either object mappings or relational mappings. Spurious mappings accounted for less than 2% of all choices in all of the experiments we performed and will not be considered further.

Figure 4 depicts the proportion of relational responses by subjects in each condition of the experiment. A one-way ANOVA was performed on the three mapping conditions excluding the familiarity control. This analysis reveals a significant difference in the level of relational responding across the conditions, $F(2,33)=3.83$, $p<.05$. As predicted, subjects in the Sim->1map condition were more likely to map on the basis of the relational structure (M=0.69)[5] than subjects in the 1map condition (M=0.42), $F(1,33)=7.30$, $p<.05$.[6] In addition, subjects were marginally more likely to map on the basis of the relations in the 3map (M=0.60) condition than subjects in the 1map condition $F(1,33)=3.50$, $.05<p<.10$. Furthermore, subjects were

[5] All condition means in this paper will be reported as mean proportions.

[6] All planned comparisons in this paper used the Bonferroni procedure unless otherwise stated.

also more likely to map on the basis of the relations in the Sim->1map condition than they were if they simply saw the scenes singly for 5 seconds (M=0.44), $t(22)=2.08$, $p<.05$.

This result is consistent with the predictions of the structural-alignment view of similarity. As we would expect if similarity comparisons involve structural alignment, subjects who rated the similarity of a pair prior to making a one-shot mapping made more relational mappings than subjects who simply performed the one-shot mapping task. Since subjects in the 3map control also made more relational responses than subjects in the 1map task, we have converging evidence that subjects in the similarity first condition mapped on the basis of the matching relational structure. Finally, subjects in the familiarity control made few relational responses, indicating that mere familiarity with the pictures is not the factor underlying the difference in relational responding between subjects in the similarity first and 1map conditions.

As a check on the consistency of these results, we can examine subjects' mappings for individual stimulus pairs. Six of the eight pairs (75%) were given more relational responses in the Sim->1map condition than in the 1map condition, p>.10 by sign test. The number of relational responses was equal in both conditions for the remaining two pairs. In addition, for five of the eight pairs (68%) subjects made more relational responses in the 3map condition than in the 1map condition, p>.10 by sign test. For two of the pairs an equal number of relational responses was given in the 3map and 1map conditions, while for one pair, more relational responses were given in the 1map condition than in the 3map condition. The general pattern of results examined by individual pairs is the same as that found in the subject analysis, but this pattern is not as strong. This weakness will be addressed in Experiment 2.

We also determined the mean rated similarity for all stimuli in each condition. These data are presented in Table 8 in the General Discussion. A one-way ANOVA showed no significant differences between conditions, $F(2,285)=1.67$, p>.10. This result suggests that subjects in different conditions did not vary substantially in their feelings about the overall similarity of the stimuli.[7]

SME as a model of comparison. The first experiment provides evidence that similarity comparisons involve structural alignment. Subjects clearly made more relational mappings in the similarity-first condition than in the 1map condition. This result was predicted on the basis of the representational assumptions described prior the experiment. In order to get a better idea of how the structural alignment process arrives at a preference for the relational match, we will now outline a more detailed set of processing assumptions that are embodied in Falkenhainer, Forbus and Gentner's (1987, 1989) Structure-Mapping Engine (SME). Then we will simulate subjects' similarity mappings using this program.

The Structure-Mapping Engine takes two propositional representations composed of *entities*, *attributes*, *relations* and *functions* and builds globally consistent matches by starting with local similarities. Entities correspond to the objects in the domains. Attributes are unary predicates that are used to give descriptive information about entities. Relations are multiplace predicates that provide information linking two or more entities or other relations. Finally, functions map one or more entities into another entity or value, and are used to represent measurements and dimensions. The critical assumption is that object descriptions and relations between objects are separable. This assumption is reflected in the use of attributes to represent local object similarities and relations to represent global connections between elements of the representation.

[7]A number of additional analyses of the data are presented in the General Discussion where the pattern across all experiments can be examined.

In the first step of the match, all identical predicates are placed in correspondence, but these local matches may not be structurally consistent. Structural consistency is then enforced by checking that matching predicates have matching arguments, while ensuring that objects in one representation map to at most one object in the other. Mappings between objects in two domains are proposed during the calculation of structural consistency when they are arguments of predicates for which a mapping has been hypothesized. Mappings between non-identical functions may be generated in this way as well. Finally, independent pieces of matching structure are grouped into maximal mutually consistent sets to form global interpretations or GMAPS. For each GMAP, candidate inferences are generated that suggest information in one domain that may carry over to the other. These inferences are based solely on the structure of the matching information. While they are useful for models of analogical transfer, it is not clear what role candidate inferences should play in similarity comparisons.

This algorithm is capable of generating all possible alternative interpretations of the match between two representations. However, it is implausible to assume that subjects consider every possible alignment between two domains. Therefore, recent research has examined the 'greedy-merge' algorithm, which produces a single interpretation that is often (but not invariably) the one that receives the highest evaluation score when all possible mappings are computed (Forbus and Oblinger, 1990). Finally, competing GMAPS are appraised using a structural evaluation function. The evaluation metric used by SME implements a preference for systematicity by starting at the highest level relational matches in the GMAP and passing evidence down to the objects via their arguments (Forbus and Gentner, 1989).

In order to simulate the Sim->1map condition from Experiment 1, we encoded the pair of scenes shown in Figure 3 in propositional form and submitted them to SME. The representations embody a number of explicit assumptions about the way subjects represent the causal scenes. First, we presupposed that subjects encode information about both the perceptual attributes of the objects as well as relations between objects and other relations. In addition, we assumed that perceptually similar objects are encoded by identical attributes, and that global relational similarities are represented as identical relational structures. We postulated that subjects encode both the central relational structure of the scene as well as other relations that are peripheral to the schema. Finally, we assumed that more higher-order relational structure is devoted to the central causal structure of a scene (e.g., that the man is giving food to the woman), than is used to encode other relations in the scene (e.g., that the tree shades the truck). Figure 5 depicts the representations used to encode the pictures in Figure 3.

We presented SME with these two representations and ran it in *exhaustive literal similarity mode*. Exhaustive means that all possible GMAPS were generated. *Literal similarity mode* allows SME to use both attributes and relations to determine the match between representations. Two of the GMAPS are depicted in Figure 6. The highest rated GMAP (evaluation score=12.94) appears in Figure 6a. This interpretation corresponds to a relational match between the scenes, and preserves the matching relational structure. Examination of the way the entities are mapped reveals that the man giving food in Figure 3a is placed in correspondence with the woman giving food in Figure 3b, while the woman receiving food in Figure 3a is placed in correspondence with the squirrel receiving food in Figure 3b. Unlike the GMAP in Figure 6a, the GMAP in Figure 6b is based on the perceptual similarity between the women in the two scenes. The identical attributes of the woman are matched, thereby placing them in correspondence. Very little of the common relational structure is preserved in this interpretation. Using

an evaluation algorithm sensitive to systematic relational structure, this GMAP receives a lower score than the relational interpretation (evaluation score=11.28), but a higher score than other possible interpretations (all of which received much lower scores). Thus, the simulation results are consistent with the patterns observed when subjects perform a similarity comparison on a pair of scenes containing cross-mappings. First, objects are placed in correspondence based on the matching relational structure rather than on the local object similarities. Second, no other alignment is at all likely.

Taken as a psychological model, the simulation results suggest that during computation of a similarity comparison, there may be active competition between a global relational match and a local object match. If so, there should be circumstances under which the local object match is preferred to the global relational match. Thus, there are two major predictions of this view. First, as tested in Experiment 1, in the presence of a cross-mapping, similarity comparisons should increase the level of relational responding over a baseline. Second, as the depth and coherence of the relational match increases, the level of relational responding should increase, but when the salience of the object match increases the level of relational responding should decrease.

Testing the structural alignment framework

This analysis suggests a global prediction space of the structural alignment view. When the relational match is poor, subjects should align the scenes based on the local object commonalities, but when the relational match is deep and coherent, subjects should align the scenes based on the relational commonalities. At intermediate levels of relational salience, more relational mappings should be made to stimuli with cross-mappings of low salience than to stimuli with cross-mappings of high salience. The experiments that follow will test these predictions.

The purpose of Experiment 2 is to explore the structural alignment framework. There are two subgoals. First, because little other work examining the importance of relational bindings, we need to replicate the findings of the first study. Second, we will test the more specific claims of the structural alignment framework by exploring the tension between object similarities and relational similarities. To this end, we will manipulate the richness of the cross-mapped objects. In the Sparse condition, the scenes will be composed of simple line drawings with no shading. In the Rich condition, the line drawings will be colored brightly, with the cross-mapped objects receiving identical colors and the other objects all receiving different colors. Thus, the salience of the object match should be higher in the Rich condition than in the Sparse condition, because these Rich cross-mappings will share an additional feature commonality (color).

As before, subjects will be run in the 1map and Sim->1map conditions. In addition, the 3map condition will be run to ensure that subjects are sensitive to the common relational structure. The key predictions focus on the contrast between the 1map condition, where subjects make only a single mapping, and the Sim->1map condition, where subjects rate the similarity of the pairs before making a relational mapping. Subjects in the Sim->1map condition should make more relational mappings than subjects in the 1map condition. However, mapping condition and object richness are expected to interact, with fewer relational responses being made in the similarity-first condition to rich stimuli than to sparse stimuli. It is not clear whether this sparse-rich difference should also hold for the 1map condition. Finally, subjects in the 3map condition should many relational responses regardless of the richness of the cross-mapped object

Figure 4

Proportion of relational responses in each Mapping condition of Experiment 1 with the causal scenes.

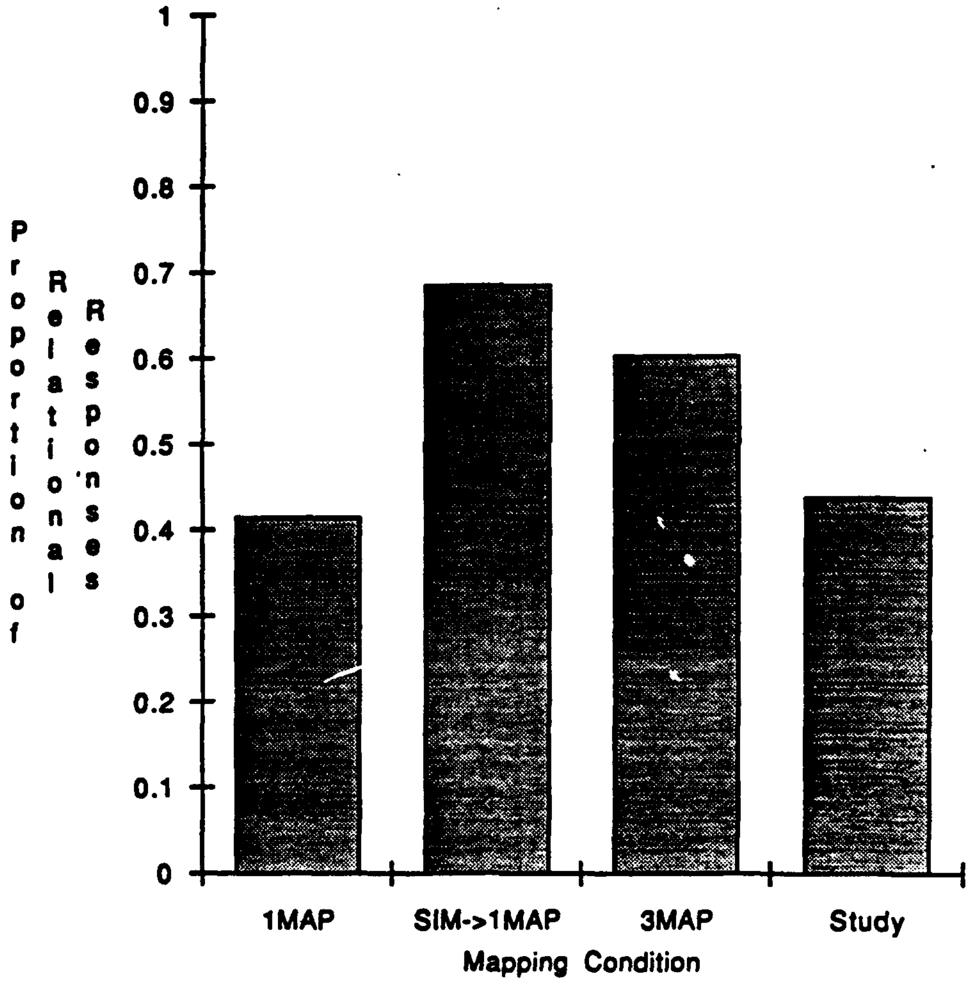
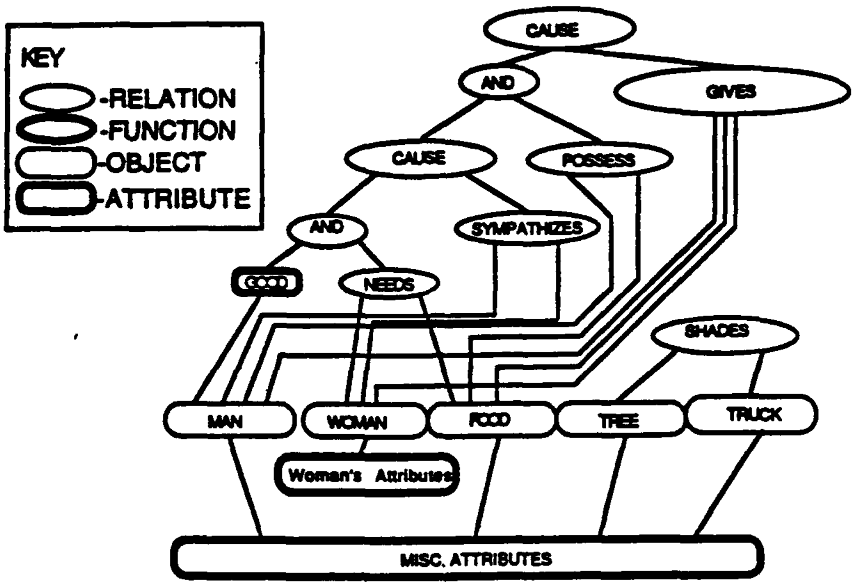
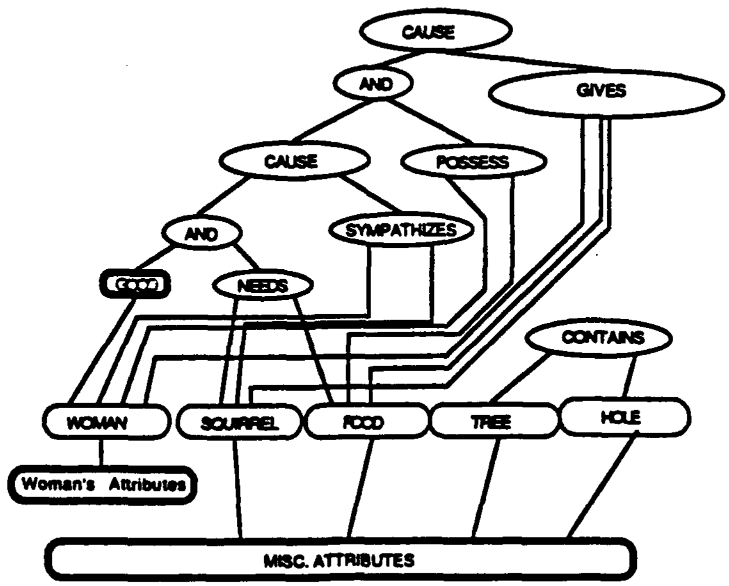


Figure 5

Relational structures given to SME in a simulation of Experiment 1. These structures represent the scenes in Figure 3.



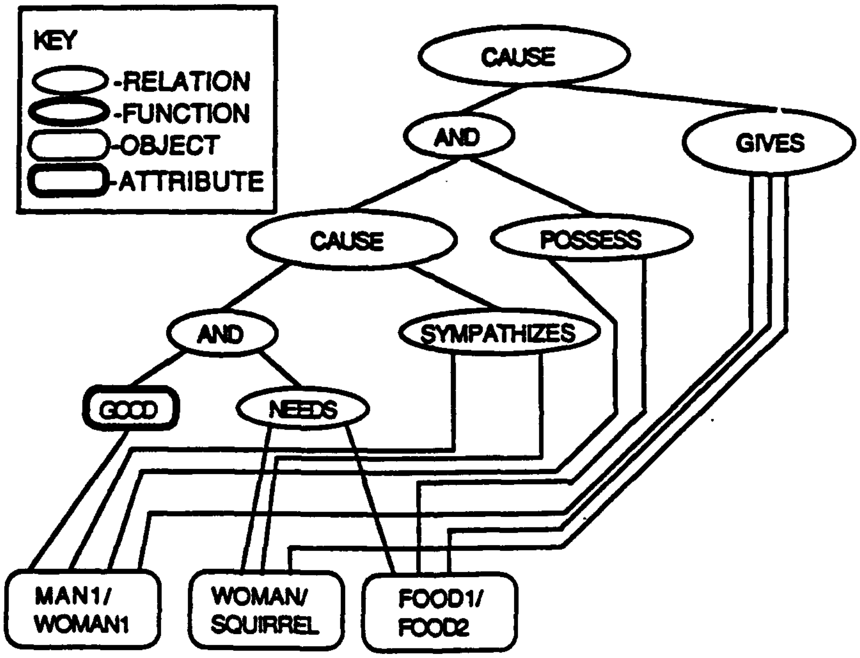
(a)



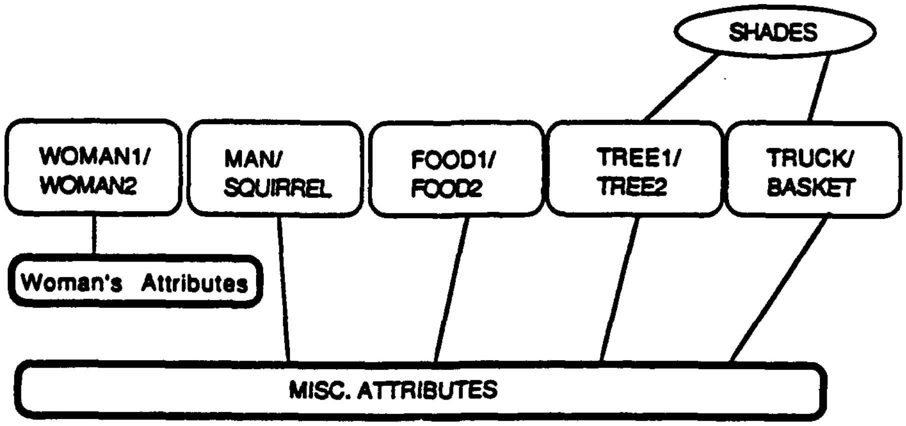
(b)

Figure 6

GMAPS arising from application of SME to the relational structures in Figure 5. The relational GMAP (a) receives a higher evaluation score than the object GMAP (b).



(a)



(b)

Experiment 2

Method

Subjects. Subjects were 72 undergraduates (12/condition) at the University of Illinois who received course credit for their participation. Subjects were run in large groups.

Design. Mapping and Richness were varied between subjects. There were three Mapping conditions(1map, 3map and Sim->1map) and two levels of Richness (line drawings (Sparse) and colored pictures (Rich)). Order of stimulus presentation was determined randomly for each subject.

Stimuli. The same eight pairs of causal scenes from Experiment 1 were used for this experiment. Two sets of these scenes were made. To create the Sparse set from the pairs used in Experiment 1, all shading was removed from the objects, leaving unshaded line drawings. To make the Rich set, the line drawings from the Sparse set were colored using markers. The cross-mapped objects in each pair received the same color. No other object in a pair had the same color as the cross-mapped object. The scenes were mounted on single sheets of paper with one scene above the other.

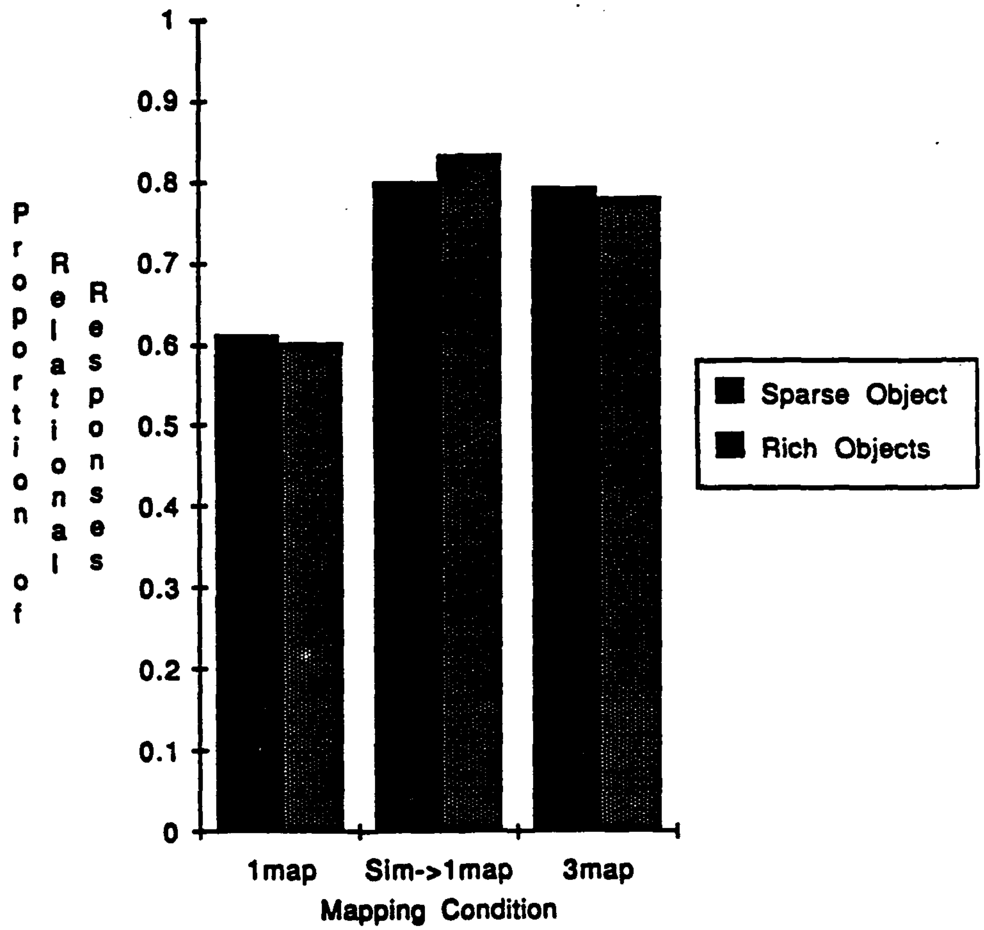
The stimuli for a given task (one-shot mapping, three mappings or similarity rating) were organized into booklets. The first page had instructions for the particular task. One stimulus pair appeared on each of the next eight pages. The color pictures were duplicated using a color photocopying process. Because of the expense of this process, the stimuli in the colored-picture condition were covered with plastic transparencies and subjects made their responses in these booklets using marking pens so that the pictures could be reused. (The experimenter recorded subjects' responses and replace the used transparency sheet with a fresh one for use by another subject.)

For stimuli in the one-shot mapping condition, the cross-mapped object in the top scene had an arrow pointing to it. In the three mapping condition, there were three arrows pointing to the cross-mapped object and two other objects taking part in the central relational structure of the top scene. For stimuli in the similarity judgment task, a line with the numbers from 1 to 9 was placed below the objects. The ends of the scale were marked 'Highly Similar' and 'Highly Dissimilar' respectively.

Procedure. Subjects received two booklets during the experiment. Subjects in the 1map condition received the one-shot mapping booklet followed by the similarity booklet, subjects in the 3map condition received the three-mappings booklet followed by the similarity booklet, and subjects in the Sim->1map condition received the similarity book followed by the one-shot mapping booklet. Thus, unlike Experiment 1, the similarity-first condition consisted of a complete block of similarity trials followed by a complete block of mapping trials. In the mapping booklets, responses were made by drawing a line from each object with an arrow pointing to it in the top scene to the object in the bottom scene they felt best went with it. In the similarity task, subjects circled the number that corresponded to their rating.

Figure 7

Proportion of relational responses in each Mapping and Richness condition in Experiment 2 with the causal scenes.



Results

The proportion of relational responses made by subjects in each condition is shown in Figure 7. A 3x2 ANOVA on these data reveals a significant main effect of Mapping Condition, $F(2,66)=4.591$, p <05. Planned comparisons between Mapping conditions indicate that, as predicted, more relational responses were made in the Sim->1map condition (M=.80 collapsed across Richness) than in the 1map condition (M=.60), $F(1,66)=6.483$, $p < .05$. Also consistent with our predictions, more relational responses were made in the 3map condition (M=.79) than in the 1map condition $F(1,66)=7.269$, $p < .05$. The 3map and Sim->1map conditions did not differ significantly. The main effect of Distinctiveness was not significant $F(1,66)=.015$, $p > .10$, nor was interaction of Mapping and Distinctiveness, $F(2,66)=.239$, $p > .10$.

The item analyses corroborate this pattern. All eight pairs (100%) received more relational responses in the Sim->1map condition than in the 1map condition, $p < .001$, sign test (one tailed). Similarly, seven of the eight pairs (87.5%) were given more relational responses in the 3map condition than in the 1map condition, $p < .05$, sign test (one-tailed). The 3map and similarity first conditions did not differ significantly; subjects gave more relational responses to five of eight (63%) of the items in the 3map condition, $p > .10$ by sign test.

Discussion

The mapping results replicated the findings of Experiment 1. Subjects who rated the similarity of a pair before performing the one-shot mapping task made more relational responses than subjects who did not rate similarity first. This result was highly stable with all eight pairs receiving more relational responses in the Sim->1map condition than in the 1map condition. In combination with the findings of Experiment 1, this finding lends support to the hypothesis that similarity comparisons involve a structural alignment process.

However, the predictions concerning the effects of object similarities were not borne out. We expected that subjects in the Sim->1map condition with Sparse stimuli would make more relational responses than subjects in the same condition with Rich stimuli. Contrary to our expectations, there was no effect of richness for these stimuli in any mapping condition. A number of alternative explanations are consistent with this finding. One possibility, of course, is that the proposed framework is misguided as to the effects of object distinctiveness. Another possibility is that the structural alignment framework is correct, but that the richness manipulation used here was not strong enough. Adding an additional attribute match to the cross-mapped objects may not have significantly increased the salience of the local match. A related possibility is that the causal relations used here may be sufficiently deep and coherent to outweigh small changes in object salience. Experiments 3 and 4 will address this issue.

Conceptual and Perceptual Relations. This brings us to the issue of the generality of the stimulus set. The results obtained in the first two experiments suggest that similarity comparisons involve structural alignment. However, it could be argued that the causal scenes used in these studies are very much like those used in experiments on analogical reasoning. That is, they embody rich causal schemas in which the objects each play identifiable and distinct relational roles. Hence, the drawings could be thought of as conceptual stimuli, even though they are pictorially presented. Furthermore, once an object is identified, its perceptual properties are not all important for its participation in a global causal structure. For example, both the woman in Figure 3a and the squirrel in Figure 3b are 'receivers,' though they look nothing alike. Finally, the scene pairs themselves contain few perceptual similarities beyond the cross-

mapped object. Thus, the results of the first two experiments may simply have confirmed that structural alignment is used to compare analogically similar pairs.

This concern gains force when we contrast the causal scenes with materials generally used in studies of similarity. Often the commonalities and differences of these stimuli are closely tied to their perceptual aspects. For example, studies of similarity have examined schematic faces (Tversky, 1977, Gati and Tversky, 1984), schematic butterflies (Goldstone, Gentner and Medin, 1989), geometric forms (Shepard, 1964), morse code signals (Rothkopf, 1957), and phonemes (Miller and Nicely, 1955, Shepard, 1974). In these materials, visual features like shading, relative size and orientation or auditory features such as duration, speed and pitch were found to be important determinants of rated similarity.

An additional reason to be concerned about the plausibility of structural alignment as a candidate for the process that compares perceptual representations is derived from a discussion by Torgerson (1965). He maintained that mental distance models of similarity are more appropriate for the analysis of similarities of perceptual stimuli than for the similarities of conceptual stimuli. In his estimation, subjects comparing perceptual stimuli tend to focus on a small number of tightly constrained dimensions, while subjects comparing conceptual stimuli make use of different background contexts and cognitive strategies. In his view, differences in the comparison process make perceptual similarities more amenable to mental-distance analysis than conceptual stimuli. On this account, evidence of structural alignment for conceptual stimuli would have no bearing on the comparison process for perceptual stimuli.

In contrast, we wish to propose that structural alignment forms the basis of similarity comparisons for both perceptual and conceptual stimuli. Of course, there may be differences in the way conceptual and perceptual scenes are processed. Subjects presented with conceptual scenes may use background and context information differently from subjects presented with perceptual scenes, but these changes are assumed to affect stages of the comparison other than mapping. For example, there may be differences in the way scenes are encoded, or the way the match is evaluated. However, the comparison process itself is expected to be the same structural alignment mechanism for perceptual pairs as for conceptual pairs.

There is some indirect support for this conjecture in studies demonstrating the importance of perceptual relations in subjects' processing of similarity. First, there is the general theoretical argument illustrated by Figure 1 that, to the extent that relations are important in the representations of perceptual materials, some mechanism for comparing relational structures, such as structural alignment, will be necessary. Empirical findings by, Lockhead (Lockhead and King, 1978) and Pomerantz (Pomerantz, Sager and Stoever, 1977) have also highlighted the importance of perceptual relations to similarity. These studies demonstrated that subjects identify configurations containing common emergent (relational) features more quickly than configurations that do not contain these features in common. Palmer (1977) presented subjects with configurations of line segments and found that subjects divided these figures into parts as would be predicted if these figures were represented by relations between perceptual units. Furthermore, Goldstone, Medin and Gentner (1990) used perceptual stimuli to demonstrate that subjects appear to separate attributes and relations into pools and give the larger pool greater weight during similarity comparisons. Finally, Ullman (1984) described a series of routines whereby the visual system could extract spatial relations to be used by other cognitive processes.

The following experiment addresses the applicability of structural alignment to perceptual

stimuli. We apply the methodology of the first two experiments to stimuli depicting perceptual relations. We expect to obtain the same relational advantage for the similarity-first condition over the 1map condition that we did for conceptual relations. In addition, we return to the predicted tradeoff between local and global similarities in the presence of a cross-mapping. We will make a more complete test of the prediction space outlined above by varying both the depth and coherence of the relational structure as well as the richness of the cross-mapping.

Experiment 3

The main aim of this study was to test whether the pattern of mapping responses found with the causal stimuli will occur for stimuli depicting perceptual relations. We used perceptual scenes in which object similarity and relational similarity were placed in opposition. Thus, this study required stimulus pairs depicting relational structure in such a way that the objects would have clear relational correspondences within that structure. In addition, the stimuli had be amenable to manipulations of the depth of matching relational structure, and to variations in the salience of the cross-mapped objects. This flexibility was needed to examine the tradeoff between object and relational commonalities. These constraints were satisfied by stimuli like those in Figure 8, which were drawn to resemble patterned rugs.

The relational structure in these stimuli was provided by multiple symmetries. Kubovy (in preparation) suggests that symmetry relations have a powerful organizational effect on the perceptual system. Kubovy refers to the particular symmetries used in these stimuli as *reflection isometries*. That is, each object in a rug had a mirror image on the other side of the rug. Objects on the left were mirror images of objects on the right, and objects on the top were mirror images of objects on the bottom. Thus, the relational match to an object was the object in the same spatial position in the other rug.[8] In these stimuli, the depth and coherence of the matching relational structure was varied by changing the number of objects in the rugs, thereby increasing the number of reflection isometries. In this study, Low Systematicity pairs contained four objects, Medium Systematicity pairs contained five objects while High Systematicity items contained at least nine objects.

In order to ensure that each object in one rug had a clear correspondence in the other, we placed 'fringes' at the narrow ends of the 'rugs.' In addition, each pair of Medium Systematicity and High Systematicity stimuli had an identical central object that was vertically symmetric which was oriented upright. These features were designed to give the rugs a clear top and bottom. Because the central objects in each pair were identical, they were expected to facilitate the relational alignment of the rugs. Finally, one pair of symmetric objects was cross-mapped in each pair of rugs. Cross-mappings were operationalized as perceptually similar pairs that occupied different relational roles (and hence spatial positions) in the patterns of the rugs.

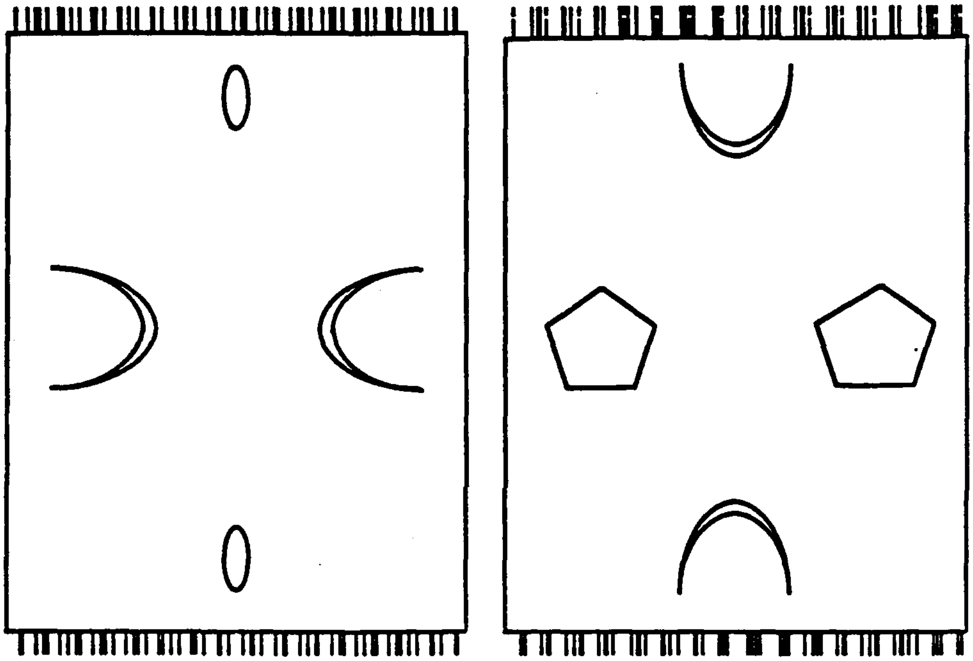
Within these basic structures, the richness of the objects was varied. Stimulus pairs contained Sparse objects or Rich objects. The objects in Sparse stimuli were simple geometric forms. These forms were unshaded, or were given uniform shading patterns. The objects in Rich stimuli were made up of complex designs and varied shadings.

[8] For the low systematicity stimuli (in Figures 8a and 8b), the relational correspondences were intentionally made to be less clear. For these stimuli, either the object in the same spatial position, or the corresponding isometric object was counted as a relational response for these stimuli.

Figure 8

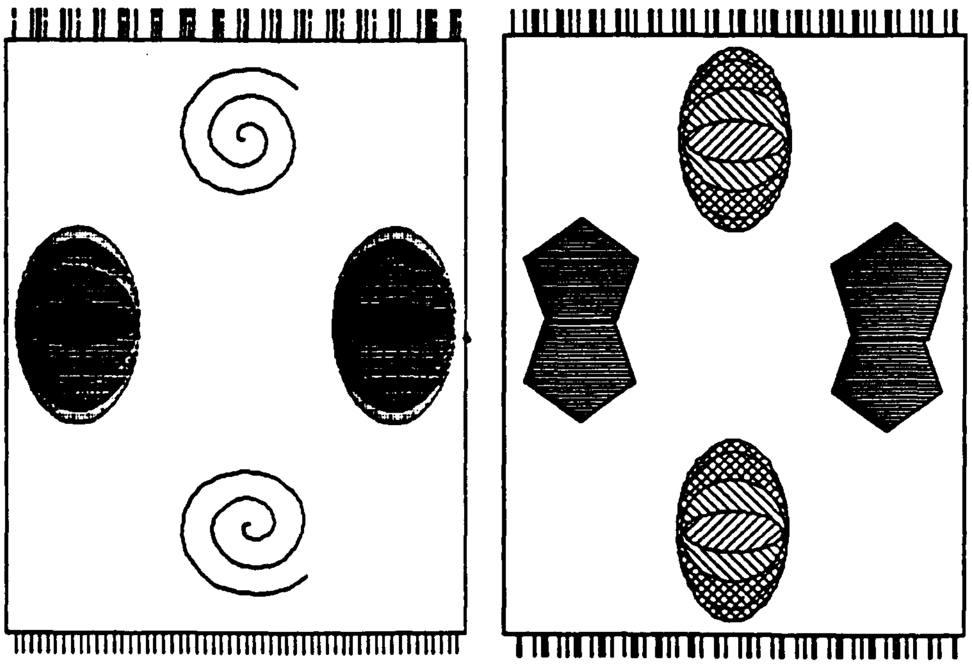
Sample perceptual stimuli resembling rugs used in Experiment 3. Two pairs of Low, Medium and High Systematicity relational structures are pictured here, one each with Sparse and Rich objects.

Sparse Low Systematicity



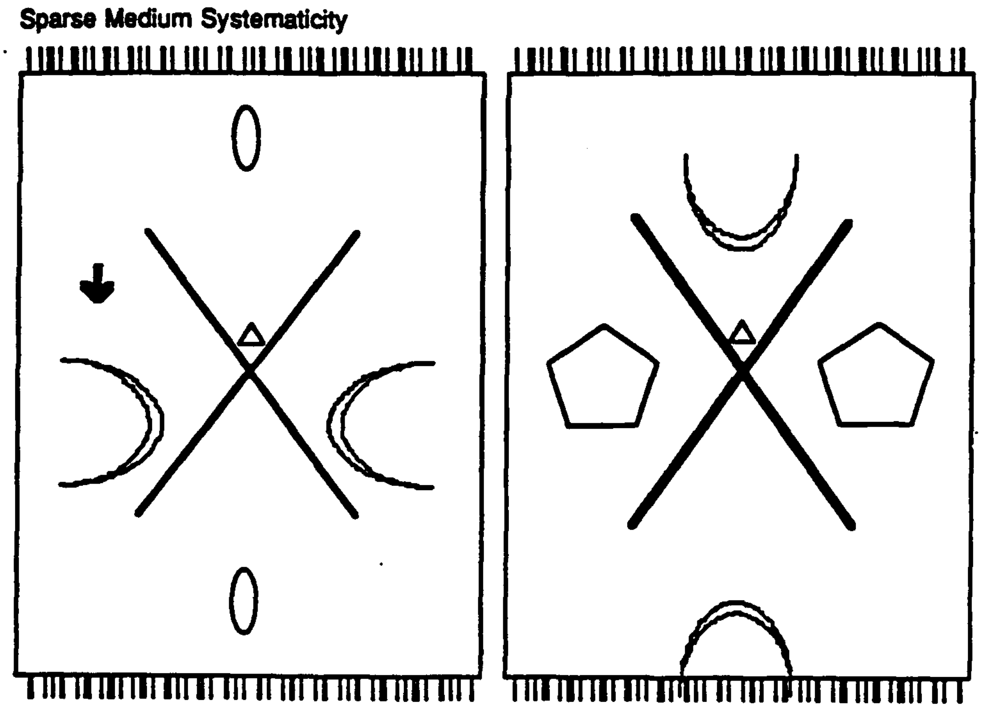
(a)

Rich Low Systematicity

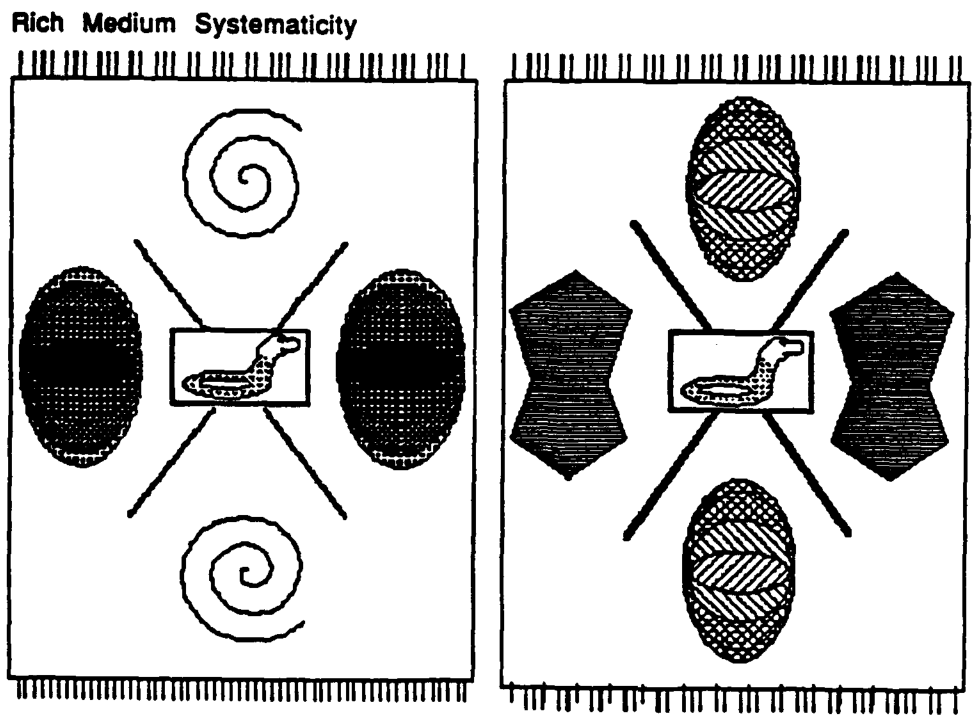


(b)

Figure 8 cont.

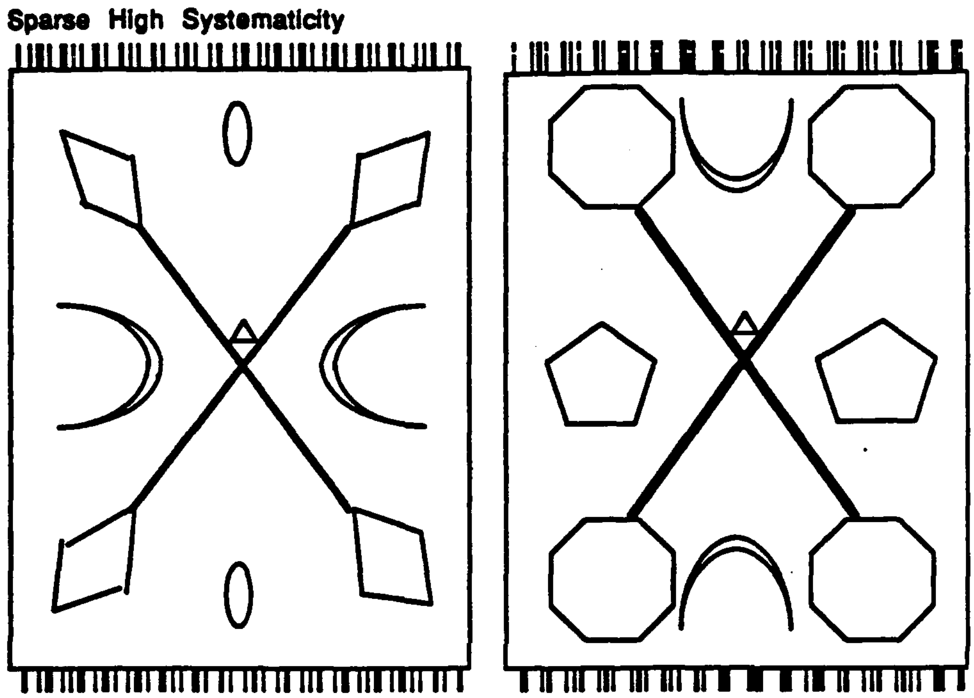


(c)

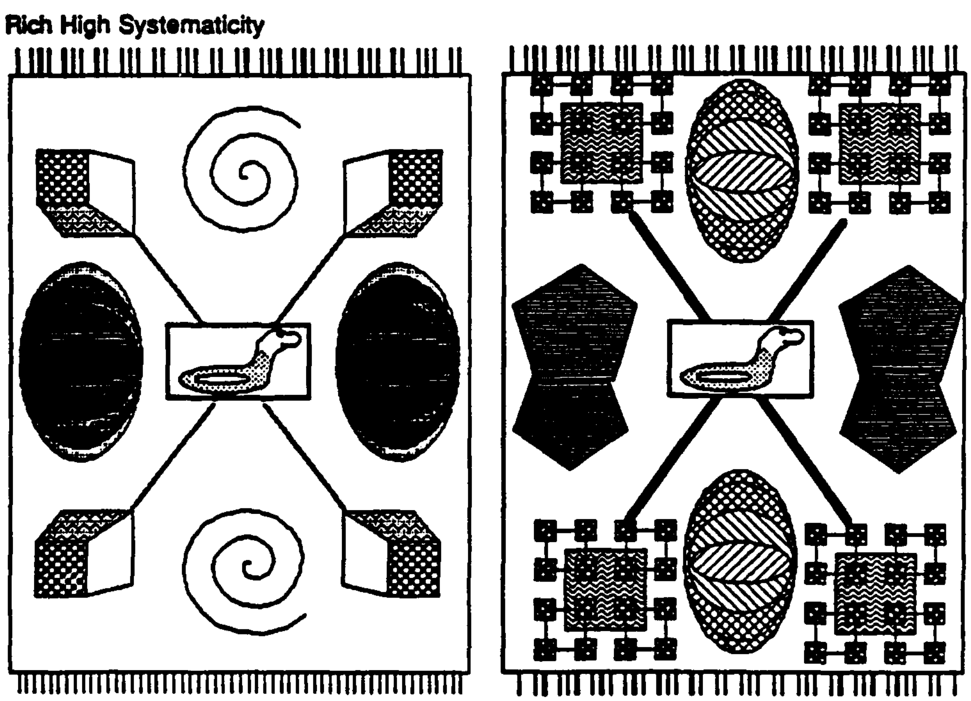


(d)

Figure 8 cont.



(e)



(f)

The most important predictions concern the contrast between the 1map and Sim->1map condition. First, the structural alignment view predicts an elevation in relational responding for subjects who rate the similarity of the scenes before mapping over subjects who simply make one-shot mappings. Second, it predicts that we should see evidence of the tension between object similarity and relational similarity. Specifically, salient local similarities are expected to have a greater effect with nonsystematic relational structures than with systematic relational structures. That is, when the objects are rich, subjects in the similarity-first condition should make more relational responses to systematic relations than to less systematic ones.

In addition, the results of the 1map condition allow us to examine the factors that affect spontaneous relational alignment. The structural alignment view makes no direct predictions for the 1map condition, but we could ask whether the factors that promote relational alignment during similarity comparisons also affect whether subjects align relational structures spontaneously. For example, subjects might be more likely to spontaneously align deep relational structures than shallow ones. Similarly, they might be more likely to spontaneously align stimuli with sparse object matches than stimuli with rich, highly salient object matches.

Method

Subjects. Subjects in this experiment were 146 undergraduates: 50 were recruited from the University of Illinois, and 96 were recruited from Northwestern University. Subjects either received course credit or were paid $1.00 for their participation in this study. Two subjects from the University of Illinois population were eliminated from this study due to experimenter error, leaving twelve subjects in each of the twelve experimental conditions.

Design. Factors in this experiment were Relational Systematicity (Low, Medium, High), Object Richness (Sparse, Rich), and Mapping Condition (1map, Sim->1map). All three factors were run between subjects.

Stimuli. Six sets of stimulus pairs were created for this experiment. Figure 8 shows a sample set. Rugs depicting shallow relations (the *Low Systematicity* figures, shown in Figures 8a and 8b) contained four objects that were placed within an oblong box with 'fringes' at the top and bottom. One object was placed along the border of the rug at the center of the top and bottom as well as at the center of the border of the rug on the right and left. The objects on the top and bottom and left and right were mirror images. One pair of objects in each pair of rugs was cross-mapped. This cross-mapping was achieved by making the top and bottom objects in one rug in a pair perceptually similar to the left and right objects in the other rug. The Medium Systematicity figures (shown in Figures 8c and 8d) were identical to the Low Systematicity ones, except that an object was placed at the center of each rug. The role of the central object was to reinforce the orientation of the rugs, and to facilitate the alignment of the two relational structures.

Six sets of High Systematicity items (pictured in Figures 8e and 8f) were also constructed by adding objects to the six Low Systematicity pairs just described. As for the Medium Systematicity figures, each of these stimuli contained central objects. One object was placed in each corner of the rug. In two of the pairs, the corner objects were attached to the center object in some way, while in the other four pictures the corner objects were separate. The corner objects were symmetric with the objects in both adjoining corners (so that all four corner objects were the same).

The components of the Sparse figures were simple geometric forms. These shapes had

uniform shadings in two of the pictures and were unshaded in four of the pictures. The central objects in these stimuli were generally single geometric shapes. The components of the Rich figures were more complex forms. Objects were given many distinct parts, each with a different shading, or possessed complex internal structure. Finally, the central objects were composed of either complex geometric forms, or detailed drawings of figures.

Two booklets were made, each containing an instruction sheet on the first page. Each booklet contained all six pairs, with each pair of rugs placed side-by side on a sheet of paper. In the mapping booklet, the rug on the left side of each page had an arrow pointing at one of the cross-mapped objects. In the similarity booklet, a similarity scale ranging from 1 to 9 was placed below each pair.

Procedure. Subjects participated in either the 1map or Sim->1map condition. These conditions differed only in the order the one-shot mapping and similarity rating tasks were performed. Subjects in the 1map condition performed one-shot mapping followed by similarity rating, while subjects in the Sim->1map condition did the reverse. Subjects in the one-shot mapping task were presented with the rug pairs with the arrows pointing to one of the cross-mapped objects. Subjects were asked to select the object in the other rug that went with that object. In the similarity judgment task, subjects were asked to rate the similarity of the rugs on the 9 point scale provided. The entire task took between 5 and 10 minutes.

Results

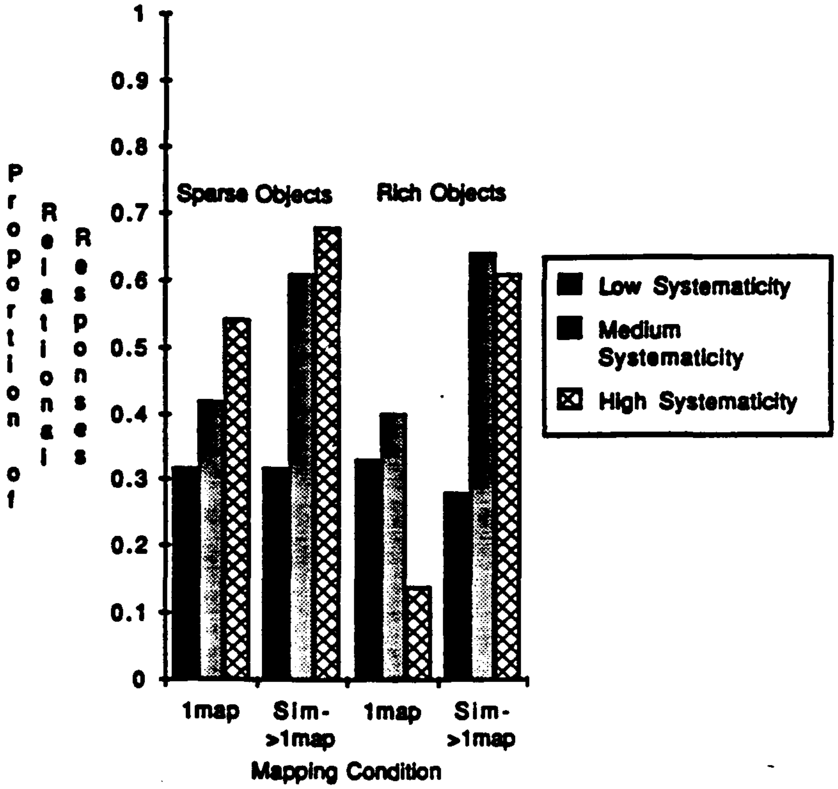
The proportions of relational responses by subjects in each Mapping and Richness condition are shown in Figure 9. As predicted, there was a significant main effect of Mapping Condition, $F(1,132)=5.78$, $p<.05$, indicating that more relational responses were made in the similarity-first condition than in the 1map condition. In addition, there was a main effect of relational depth, $F(2,132)=4.15$, $p<.05$. Planned comparisons indicate that fewer relational responses were made to the Low Systematicity stimuli (M=0.32) than to the Medium Systematicity stimuli (M=0.52), $F(1,132)= 7.21$, $p<.01$ or the High Systematicity stimuli (M=0.49), $F(1,132)=5.07$, .05¡p <.10. The main effect of Richness did not achieve significance, $F(1,132)=1.81$, $p>.10$, nor did any of the interactions.

Visual inspection of the data suggests that the relational advantage of the Sim->1map condition arises primarily for the Medium and High Systematicity pairs. For the Medium Systematicity pairs, there was a tendency for subjects to make more relational responses in the Sim->1map (M=0.63) condition than in the 1map condition (M=0.41). Similarly, for the High Systematicity pairs, there was a tendency for subjects to make more relational responses in the Sim->1map condition (M=0.65) than in the 1map condition (M=0.34). However, for the Low Systematicity pairs, roughly the same proportion of relational responses were made in both the Sim->1map (M=0.31) and 1map (M=0.32) conditions.

This visual inspection does bring out one anomalous point. In general, as the Systematicity of the pairs increases, the number of relational responses made to the pair increases as well. However, this pattern is broken for the Rich items in the 1map condition where fewer relational responses (M=0.14) were made to High Systematicity pairs than to either Low Systematicity pairs (M=0.33) or Medium Systematicity pairs (M=0.40). Indeed, a subject analysis of this condition indicates that 6 of the 10 relational responses made by subjects in this condition were made by a single subject. We will examine this result below.

Figure 9

Proportion of relational responses in each Mapping, Richness and Depth condition of Experiment 3 with perceptual relations.



Item analyses corroborate the overall findings of the data analyzed by subjects. Including both levels of Richness, more relational responses were made to 2/12 (17%) of the Low Systematicity pairs in the similarity-first condition than in the 1map condition. However, more relational responses were made to 11/12 (92%) and 12/12 (100%) of the Medium and High Systematicity pairs (respectively) in the similarity-first condition than in the 1map condition. Once again, the item analyses reveal that few relational responses were made to Rich High Systematicity pairs in the 1map condition.

Discussion

The key finding of this study was that, as predicted, subjects made more relational responses in the similarity-first condition than in the 1map condition. This relational advantage was particularly evident for the Medium Systematicity and High Systematicity items. Thus, this experiment provides evidence that even similarity comparisons involving perceptual relations involve structural alignment. However, subjects' performance with the Low Systematicity pairs supports the claim that both object similarity and relational similarity are involved in alignment. In this condition, for which the relational match was poor, even subjects in the similarity-first condition often mapped on the basis of the object similarity.

There are two related puzzling aspects of the data. First, the data did not support the prediction that Rich objects would lead to more object mappings than Sparse objects. Second, the only condition that was affects by object richness was the 1map condition with Highly Systematic relations. In this condition, subjects made fewer relational responses to Rich items (M=0.14) than to Sparse items (M=0.54).[9] One possible explanation for this phenomenon is suggested by inspection of these items (like the pair in Figures 8e and 8f). The addition of objects to create the deep and coherent relational structures may actually have obscured the relational structure, making these pairs appear to be a complex web of objects. The salient object similarity of the Rich objects then leaps out of this mass. However, when asked to rate similarity, subjects noticed the salient relational match between the scenes, and made relational responses. This finding hints that similarity comparisons highlight salient relational commonalities of stimuli by forcing subjects to look for a global match between scenes. A similar point has been raised by Medin, Goldstone and Gentner (in preparation) who presented subjects with pairs of figures, one of which contained some ambiguity. In this study, subjects appear to create new features of the ambiguous item in an effort to maximize the commonalities of a pair.

Returning to the first puzzling aspect of the data, we must explain why Richness did not affect the Sim->1map condition. This finding is surprising in light of previous work that has demonstrated that rich cross-mappings make the determination of relational correspondences more difficult. Gentner and Toupin (1986) found that children had difficulty aligning a matching relational structure when the cross-mapped objects were highly distinctive. Furthermore, Rattermann and Gentner (1990) carried out an explicit richness manipulation. Using a mapping task in which the task was to select an object based on relational similarities, they demonstrated that children find it harder to align matching relational structures when the cross-mappings are rich than when they are sparse.

[9] We replicated this result. In the replication, subjects in the 1map condition made fewer relational responses to Rich items (mean=0.22) than to Shallow items (mean=0.68) giving us confidence that this finding is not simply due to chance (Markman, 1992).

A deeper examination of the stimuli from these previous studies reveals a possible explanation for the differences between the results of previous studies and those presented here. In Gentner and Toupin's studies, all three of the objects were cross-mapped, and subjects made many object mappings. Similarly, in the work by Rattermann and Gentner, two of the three objects were cross-mapped and many object mappings were made. However, in the stimuli in this study (as well as in Experiment 2), only a single object was cross-mapped, and few object responses were made. It is possible that, during similarity comparisons, subjects may notice the powerful object similarity of a highly distinctive cross-mapped object, but may choose not to make their mappings based on this similarity because it does not provide a basis for aligning any of the other objects. Thus, the salience of the local similarities may only affect subjects' mappings when a global interpretation based on local similarities allows more than one of the objects to be placed in correspondence. We will examine this possibility in the final experiment using stimuli depicting the monotonic increase and symmetry relations that have been used in previous studies of similarity (Rattermann and Gentner, 1990, in preparation Kotovsky and Gentner, 1990).

The *symmetry* relation is operationalized a central object with identical objects on either side (i.e., 131 or 323). The *monotonic increase* relation is operationalized as three objects increasing in size or darkness from left to right or right to left (i.e., 134 or 542). In our studies, the three objects in each scene are identical except for differences along either the size or darkness (color saturation) dimension. Sample stimulus pairs depicting the symmetry relation are shown in Figures 10a and 10c, while sample pairs depicting the monotonic increase relation are presented in Figures 10b and 10d.

As in the previous studies, each pair of scenes in this experiment contained a cross-mapped object. However, unlike the stimuli in these studies, the objects that were not cross-mapped were also perceptually similar to each other. Thus, if subjects decided to place the cross-mapped objects in correspondence, they could also align the other objects on the basis of perceptual similarities. With these stimuli, we could vary the richness of the objects making up the relational structure. The Sparse stimuli were constructed from either circles or squares colored some shade of grey. We assumed that these simple geometric forms would not be tempting object matches. In contrast, the Rich stimuli were constructed from objects like palm trees and houses. These objects were colored one of six different hues with each object in an array colored identically. We presupposed that the Rich objects would be more tempting object matches.

This richness manipulation is different from the ones in Experiments 2 and 3. In the previous studies, adding matching attributes to the cross-mapped objects increased their similarity to each other, while simultaneously decreasing their similarity to the rest of the objects in the scenes. Thus, the richness manipulation in these studies was a manipulation of *distinctiveness*. In contrast, in this study, the increase in the number of matching attributes of the cross-mapped objects also increased the number of attributes that matched with all of the objects in the scenes, thereby increasing the *overlap* in the attributes of the stimuli.

To review our predictions, few relational responses should be made in the 1map condition. An elevation in relational responding should be observed for the Sim->1map condition relative to the 1map condition, since the similarity judgment should make subjects more sensitive to the matching relational structure. In addition, more relational responses should be made to Sparse stimuli than to Rich stimuli. It is not clear whether this relational advantage for Sparse stimuli should be greater for the 1map condition, in which spontaneous alignment may be more likely

when objects are sparse, or in the similarity first condition, in which salient object similarities should lead to a low level of relational responding. Finally, many relational responses should be made in the 3map control regardless of the richness of the objects.

Experiment 4

Method

Subjects. Subjects were 50 undergraduates at the University of Illinois, who received course credit in introductory psychology for their participation. Two subjects were eliminated from the study for failing to follow instructions, leaving a total of forty-eight (eight/condition).

Design. There are three Mapping conditions and two levels of Richness (Sparse and Rich). Both factors were between-subjects.

Stimuli. The stimuli were sixteen pairs of pictures of perceptual relations, like those shown in Figure 10. Symmetry relations were operationalized as an array of objects containing a central object flanked by identical objects. We will use the following naming convention: if the outer objects are smaller or lighter than the central object, the relation is of *positive polarity*. If the outer objects are larger or darker than the central object, then the relation is of *negative polarity*. A pair of stimuli displaying the symmetry relation can have the same polarity (i.e., positive/positive or negative/negative) or opposite polarity (i.e., positive/negative or negative/positive).

Stimuli displaying the monotonic increase relation were similarly organized. The relation was operationalized as a series of three objects increasing, either in height or in color saturation, from left to right or right to left. The relation is of *positive polarity* if the increase takes place from left to right and of *negative polarity* if the increase takes place from right to left. As for pairs displaying symmetry, pairs displaying the monotonic increase relation can be of the same polarity or of opposite polarity.

Half of the pairs depicted symmetry relations and half depicted monotonic increase relations. Half of the pairs were of the same polarity and half were of opposite polarity. Finally, in half the pairs, the objects varied in size, while in half of the pairs, the objects varied in saturation. These three presentation factors were fully counterbalanced. There were two examples of each combination of the three factors in the set of sixteen pairs. A summary of the structure of the stimulus set is presented in Table 2.

The stimuli were presented on a Macintosh II color computer screen. In the sparse condition, the stimuli consisted of either circles or squares displaying either symmetry or monotonic increase. Six easily discriminable shades of grey were generated by using equal levels of red, green and blue at 15, 30, 45, 60, 75 and 100% saturation. In addition, five easily discriminable object sizes were used, (radii of 3, 6, 12, 24 and 48 pixels).

The Rich objects were constructed similarly, except that the objects (house, globe, investi gator, scale, palm-tree and light bulb) were taken from a public-domain set of clip art for the Macintosh Computer. Five distinct sizes of these objects were made. In addition, six saturation levels of six hues were used (black, red, green, blue, turquoise and yellow). Hue was arbitrarily paired with shape between items. Within a given array, all items were the same shape and hue. In addition, within an array, all items were identical except along the dimension along which the symmetry or montonic increase relation occurred. Within a stimulus pair, all items were of the same shape and hue.

Figure 10

Sample monotonic increase and symmetry stimuli, like those used in Experiment 4. Sample Sparse (a and b) and Rich (c and d) stimuli are shown.

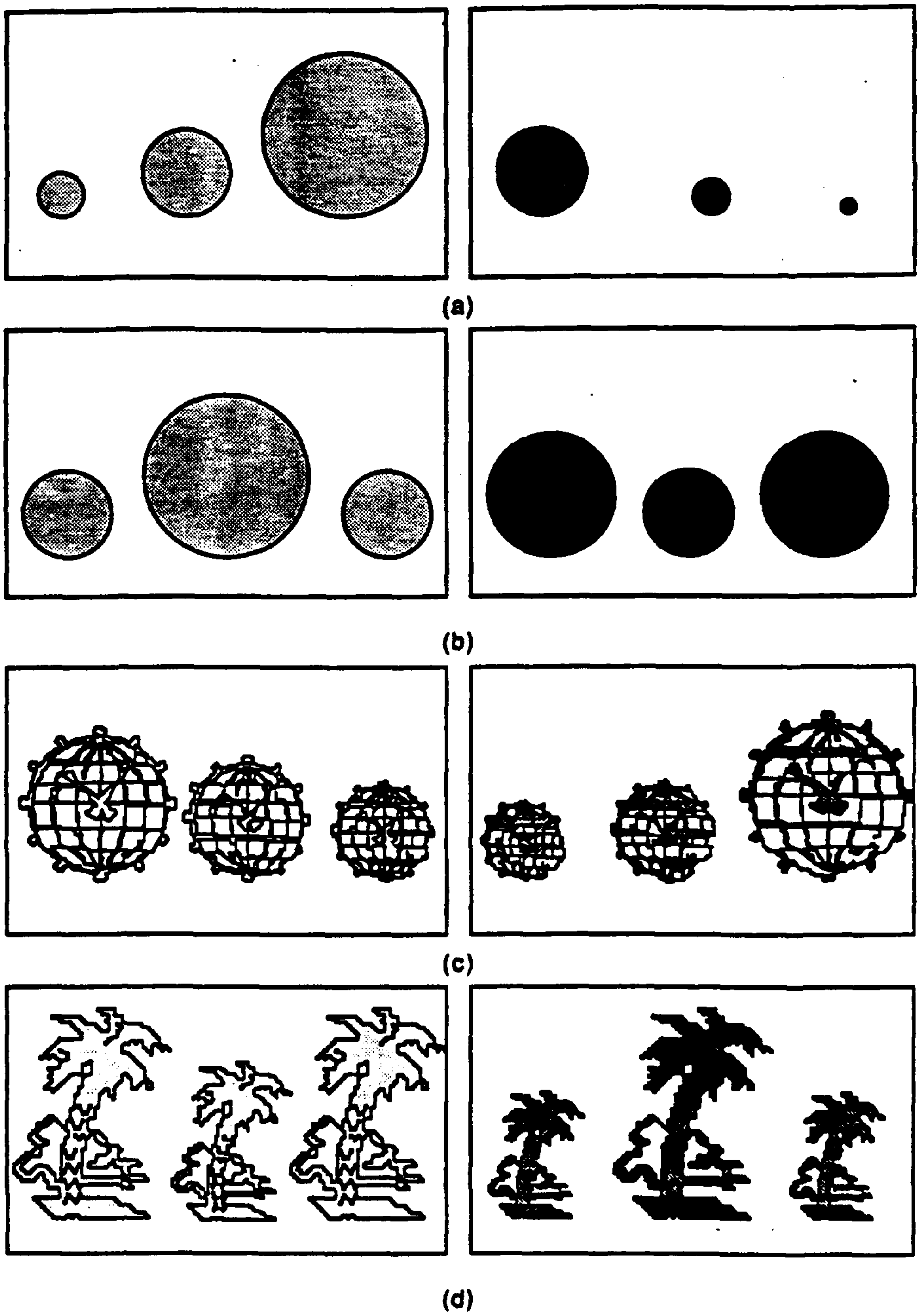


Table 2
Structure of Geometric Stimuli Used in Experiment 4

	Stimulus Dimensions		
Stimulus	Relation	Polarity	Varies in
1	Monotonicity	Same	Color
2	Monotonicity	Same	Size
3	Monotonicity	Same	Color
4	Monotonicity	Same	Size
5	Monotonicity	Opposite	Color
6	Monotonicity	Opposite	Size
7	Monotonicity	Opposite	Color
8	Monotonicity	Opposite	Size
9	Symmetry	Same	Color
10	Symmetry	Same	Size
11	Symmetry	Same	Color
12	Symmetry	Same	Size
13	Symmetry	Opposite	Color
14	Symmetry	Opposite	Size
15	Symmetry	Opposite	Color
16	Symmetry	Opposite	Size

Each pair of scenes contained a cross-mapping, operationalized as a pair of perceptually similar objects in the two scenes that played different roles in the relational structure in each scene. In order to create this perceptual similarity, the objects were identical along the dimension varying in the relation size or saturation), but slightly different along the dimension irrelevant to the relational structure.

Procedure. Subjects were run one at a time using a Macintosh II computer. The program for running the experiment was written in the cT language (Sherwood and Sherwood, 1988). In the mapping portion of the study, subjects were told that they would see two scenes. An arrow would appear over one of the objects in the top scene and they were to select the object that best 'goes with' that object by moving a cursor on the screen with the mouse and clicking on the preferred object. In order to get subjects comfortable with this use of the mouse to choose objects, they were given practice trials in which scene would appear on the screen, and they were told to select either the right, middle or left object.

On the computer, the basic one-shot mapping task took the following form. At the beginning of each trial, a small (20 pixel x 10 pixel) box appeared at the top center of the screen. Subjects were told to move the cursor inside of the box and click. This was done to ensure that the cursor was always centered at the start of a trial. When the subject clicked in the box, it disappeared and a fixation point appeared at the center of the screen for 500ms. Then the two scenes appeared, presented one above the other. An arrow pointed at the cross-mapped object in the top scene. The trial ended when the subject selected one of the objects in the bottom

scene. The subject's choice was recorded. If subjects clicked on an object in the top scene or outside of the scene boxes they were told to select again. After their selection, the scenes were erased, another fixation point appeared for 1500 ms, and the next trial began.

The three-mappings task was identical to the one-shot mapping task, except that subjects were told initially that they would be asked to perform a mapping for all three objects in a scene. After the first mapping (for the cross-mapped object), the first arrow disappeared and a second arrow was placed over a different object in the top scene. When the subject selected another object in the bottom scene, the second arrow disappeared and a third arrow was drawn over the last object and subjects made a third mapping. All three responses were recorded.

In the similarity part of the experiment, subjects were told to rate the similarity of the pairs of scenes they would see on a scale from 1 (low) to 9 (high). The pairs were presented one at a time and the subjects were asked to type in their rating from the computer keyboard. The trial ended when the subject entered their rating. Then a fixation point appeared for 1500 ms and the next trial began. Subjects' similarity ratings for each pair were recorded.

Subjects in the 1map condition performed the one-shot mapping task followed by the similarity ratings task. Subjects in the Sim->1map condition performed a block of similarity ratings before performing the one-shot mapping task. Finally, subjects in the 3map condition performed the three-mappings task followed by the similarity ratings task.

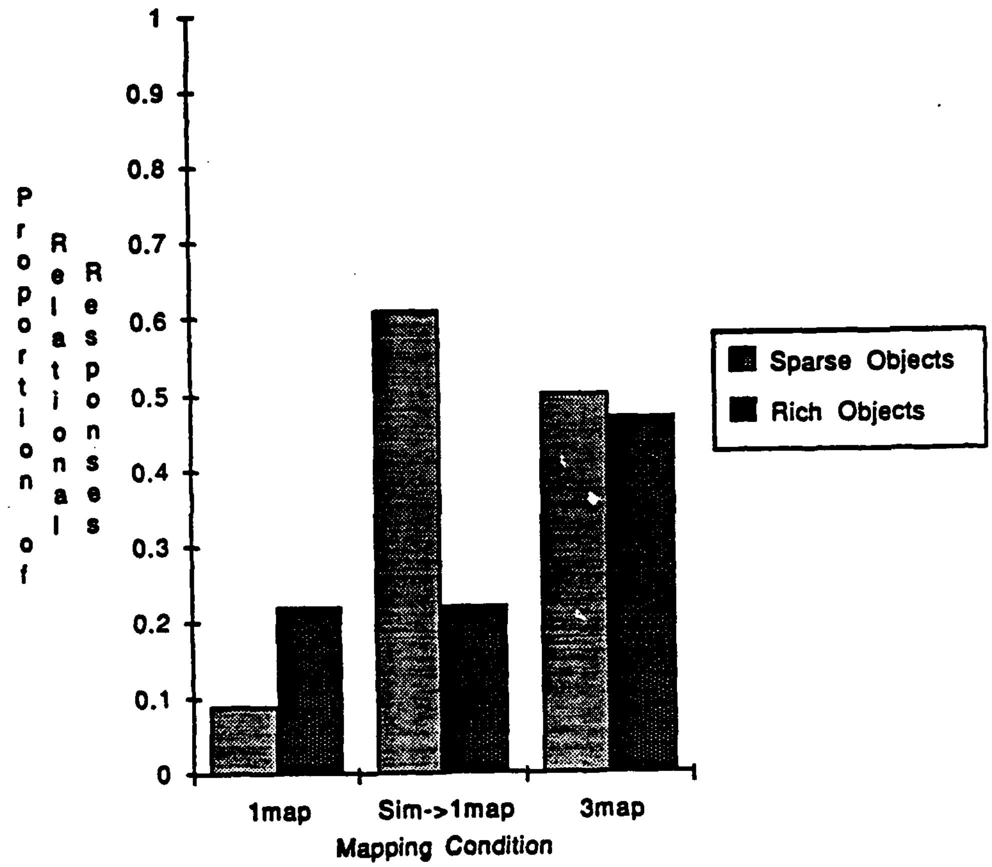
Results

The proportion of relational responses made by subjects in each Mapping and Richness condition is shown in Figure 11. As predicted, there was a significant main effect of Mapping condition $F(2,42)=6.40, p<.005$. The main effect of Richness was not significant $F(1,42)=1.11$, p>.10. Also as predicted, there was a significant Richness x Mapping interaction $F(2,42)=4.07$, $p<.05$. This interaction reflects that more relational responses were made to Sparse items in the Sim->1map condition (M=0.61) than in the 1map condition (M=0.09), $t(14)=3.44$, $p<.01$, but the same number of relational responses was made to the Rich objects in the Sim->1map condition (M=0.22) and 1map condition (M=0.22).

Examination of the individual items provides corroboration for the observed interaction. More relational responses were made in the Sim->1map condition than in the 1map condition for all sixteen Sparse stimuli (100%), $p<.001$ by sign test. However, only 5/16 (31%) of the Rich items received more relational responses in the Sim->1map condition than in the 1map condition, p>.10 by sign test. In addition, more relational responses were made in the 3map condition than in the 1map condition for all sixteen items (100%) for both the Sparse and Rich stimuli $p<.001$ by sign test.

Figure 11

Proportion of relational responses in each Mapping and Richness condition of Experiment 4 within perceptual relations containing many object similarities.



Discussion

The tension between object and relational similarity. This study provides additional evidence that similarity comparisons involve relational alignment. More relational responses were made in the similarity-first condition than in the 1map condition for the Sparse stimuli. In addition, this study provides evidence that salient local similarities can cause subjects to align scenes based on object similarities. The same number of relational responses were made in the Sim->1map condition and 1map condition for Rich stimuli. This finding suggests that subjects do make global mappings based on object similarities when this interpretation allows many of the objects to be mapped. However, there is one anomaly in these results. More relational responses were made in the 1map condition to Rich objects than to Sparse objects. Although this difference was not significant, we would have expected it to be in the opposite direction.

Alternate interpretations. We have interpreted the results of the Sparse condition as evidence that similarity comparisons can promote a sensitivity to the common relational structure. However, it could be argued that subjects in the similarity-first and 3map conditions were selecting the object in the bottom scene that occupied the same relative spatial position as the cross-mapped object, as opposed to matching on the basis of the same relational role. Although relative position could be considered relational, this account would clearly be different than if subjects were mapping on the basis of the monotonic increase and symmetry relations. We can examine this explanation with respect to the Sparse stimuli.

For most of the stimuli in this set, relational role and spatial position are correlated. Fortunately, in one of our stimulus types, monotonic increase relations of opposite polarity (items 5 through 8) relational structure is separated from relative position. Thus, if subjects select the relational mapping for these stimuli, we can reject the possibility that their mappings simply reflect a preference for relative spatial position. For these stimuli, subjects made a greater proportion of relational mappings in the similarity first condition (mean=0.50) than in the 1map condition (mean=0.09). Furthermore, the proportion of relational responses in the Sim->1map condition for these items (0.50) is comparable to the proportion of relational responses to the rest of the stimuli in the similarity-first condition (0.65). Finally, subjects who did not make a relational response tended to map based on object similarities, not positional similarities. These results support the claim that subjects were mapping on the basis of the matching relational structure, not spatial position.

Another possible explanation for the results in the Sparse condition is that subjects attempted to minimize the global dissimilarity between objects placed in correspondence, while still respecting the one-to-one mapping constraint.[10] By this account, relational alignment would play no role in their processing. For example, if the objects in a pair of monotonic-increase stimuli are placed in the same correspondences as are dictated by aligning the relational structure, the pairwise similarities are maximized. Each pair of objects differs slightly, but any other way of aligning the scenes would place two highly dissimilar objects in correspondence. This interpretation does not hold for symmetry relations of opposite polarity (items 13 through 16), where the relational mapping requires that dissimilar objects be placed in correspondence. Examination of subjects' performance on these items indicates that their level of relational responding (mean=0.53) is about the same as the level observed for all other stimuli (mean=0.61). Furthermore, more relational responses were made to all four symmetry relations of opposite polarity in the Sim->1map condition than in the 1map condition. Thus, it appears

[10] We would like to thank Doug Medin for raising this possibility.

that the increase in relational responding in the similarity-first condition for Sparse stimuli was not due merely to minimizing overall object dissimilarity.

Analysis of Presentation Factors. These perceptual stimuli afforded us the opportunity to control the type of relation, polarity and dimension along which the items differed (see Table 2). Analysis of the Sim->1map condition with Sparse stimuli allows us to assess these factors in a task which we assume promotes relational mapping. The type of relation did not appear to matter: subjects made the same proportion of relational responses to stimuli depicting the monotonic increase and symmetry relations (mean=0.61 for both relations). Consistent with our intuitions, there was a tendency for subjects to make a higher proportion of relational responses to stimuli of the same polarity (0.67) than for stimuli of opposite polarity (0.54). Kotovsky and Gentner (in preparation) found the same result for 4, 6 and 8 year olds. Furthermore, Goldstone and Gentner in an unpublished pilot study also found an advantage for same polarity stimuli. Subjects also made a higher proportion of relational responses for stimuli varying in size (0.70) than for stimuli varying in color (0.51). This result meshes with findings by Smith and Sera (1992) that the size dimension has clear 'more' and 'less' directions for adults, while the darkness dimension does not.[11]

General Discussion

The four experiments presented here provide overall support for the hypothesis that similarity comparisons involve a structural alignment of scene representations. According to this proposal, when a pair is compared, objects can be placed in correspondence if they share common local properties or play common roles within a matching relational structure. The result of the alignment process is a structurally consistent mapping that can be used to determine a pair's commonalities and differences.

The plausibility of this view was assessed with the one-shot mapping technique. In the basic one-shot mapping task, object similarities and relational similarities were placed in opposition with a cross-mapping, and subjects were asked to select the object in one scene that went with the cross-mapped object in the other scene. In the crucial experimental manipulation, subjects were asked to rate the similarity of the scenes prior to making a one-shot mapping. If similarity comparisons promote structural alignment, then it was expected that the similarity-first condition would show elevated levels of relational responding relative to the 1map condition.

These predictions were illustrated in an SME simulation of similarity comparisons of stimuli containing cross mappings. This simulation indicated that the preference for the relational match in a similarity comparison arises from a competition between a match based on object similarities and a match based on relational similarities. Because an object and a relational interpretation compete, it was further predicted that increasing the salience of the relational match would increase subjects' level of relational responding, while increasing the salience of the local object similarities would decrease subjects' level of relational responding.

[11] Goldstone, Gentner and Medin (1989) obtained a similar result.

Does similarity promote structural alignment?

Our chief prediction was that similarity comparisons make subjects sensitive to the matching relational structure. The data for all studies are summarized in Table 3. The structural alignment view predicted a relational advantage for the Sim->1map condition over the 1map condition. In 7/10 comparisons presented in this table, the percentage gain in relational responses from the 1map to the Sim->1map condition was at least 25%, and it was as high as 578% for the Sparse objects in Experiment 4. This finding is encouraging, because all we asked subjects to do was rate the similarity of the pairs on a nine point scale. We gave no instructions about how similarity should be determined. Nevertheless, this simple task led subjects who rated similarity first to make more relational mappings than subjects who did not compare the scenes prior to the one-shot mapping task. These findings provide evidence that objects are placed in correspondence based on their position within the matching relational structure during a similarity comparison.

Table 3
Summary of results across experiments

Experiment	Degree Spontaneous Alignment(a)	Alignment in Sim>1map Condition(b)	Percentage Gain from 1map to Sim>1map
1	0.42	0.69	64
2	0.60	0.80	33
3:S/S (c)	0.32	0.32	0
3:S/R	0.33	0.28	-1
3:M/S	0.46	0.61	33
3:M/R	0.40	0.64	60
3:D/S	0.54	0.68	26
3:D/R	0.14	0.61	335
4:Sparse	0.09	0.61	578
4:Rich	0.22	0.22	0

(a) Level of relational responses in 1map condition
(b) Number of relational responses in Sim>1map condition
(c) For Experiment 3: S/-Shallow, M/-Medium and D/-Deep Relations, /S-Sparse and /R, Rich objects.

Contrary to the main prediction, no relational gain was found in three of the comparisons between 1map and similarity-first conditions. First, in Experiment 3, subjects presented with Low Systematicity relations made roughly the same number of relational responses in both the 1map and Sim->1map conditions. However, these stimuli were explicitly designed to have relational structures of low salience. The more detailed predictions derived from the SME simulation of one-shot mappings suggest that subjects should make few relational responses when the relational match is of low salience.

In addition to the Low Systematicity conditions of Experiment 3, the Rich conditions in Experiment 4 also failed to show a relational advantage for the Sim->1map condition. These stimuli consisted of monotonic increase and symmetry relations composed of rich figures, and were designed to heighten the salience of the local commonalities in a manner consistent with the studies of Gentner and Toupin (1986) and Rattermann and Gentner (in preparation), where there were multiple object similarities. Because of the high salience of the object similarities in these stimuli, it was expected that the relational advantage for the similarity-first condition would be markedly decreased. Indeed, as predicted, no relational advantage was observed for these stimuli.

Effects of object similarity

We can examine the effects of object similarities on the mapping process in more detail. It was predicted that salient local similarities would increase subjects' tendency to map on the basis of object commonalities during a similarity comparison. The evidence for this prediction was less robust than the evidence that similarity promotes structural alignment. In support of this conjecture, no relational advantage was observed for the similarity-first condition for the Rich objects in Experiment 4. In this study, all of the objects shared overlapping attributes, thereby allowing all three objects in each array to be placed in correspondence based on local similarities.

Contrary to our predictions, subjects' performance in the similarity first condition was not affected by the highly distinctive cross-mapped objects in Experiments 2 and 3. The manipulation of distinctiveness made the cross-mapped objects both more similar to each other and more different from all of the other objects in the pair. When the cross-mapped objects are placed in correspondence based on their similarity, there is no basis for aligning the rest of the objects in the scenes, because they are perceptually dissimilar. However, in all experiments, the relational match allowed at least three objects in each scene to be placed in correspondence. Thus, even though subjects may have noticed the object similarity, they may have felt that similarity comparisons should account for as many commonalities as possible (Sjoberg, 1972, Krumhansl, 1978), thereby leading to a preference for the more global relational match.

Although distinctiveness did not appear to affect subjects' relational mappings in the similarity-first condition, the distinctiveness manipulation did affect subjects' performance in the 1map condition of Experiment 3. In this study, subjects in the 1map condition made fewer relational responses to rich items (M=0.31) than to sparse items (M=0.58). Since the 1map only requires subjects to find a correspondence for the cross-mapped object, subjects in this condition might be expected to be more sensitive to local commonalities than subjects in the similarity-first condition.

Structural alignment and relational depth

The structural alignment view predicts that, holding object similarity constant, the higher the salience of the relational match, the greater the likelihood of a relational mapping. In these studies, we expected more relational responses to be made when the relations were deep and coherent, than when the relations were shallow and incoherent. This prediction is most strongly supported by the results of Experiment 3, where (collapsing across richness) more relational responses were made to High Systematicity items (M=0.65) and Medium Systematicity items (M=0.63) than to Low Systematicity items (M=0.32) in the similarity-first condition.

Within the context of a computational model of structural alignment, like SME, relational depth can be defined simply as the order of the relations. Similarly, coherence can be defined as the overall interconnectivity of the relations (i.e., the *relational density* (Gentner, 1981)). While these factors may clearly increase the salience of a relational match within a computational model, defining the actual stimulus properties that correspond to depth and density is a more difficult task. Ritov, Gati and Tversky (1990) addressed this issue by ostensively defining certain stimulus manipulations as making items more cohesive. However, the precise stimulus properties that instantiate depth, coherence and cohesiveness is an open research question.

Spontaneous Relational Alignment

Although explicit similarity comparisons lead to the alignment of relational structures, we might speculate about how often representations are spontaneously aligned. In the context of these studies, we can interpret the results of the 1map condition (summarized in Table 3) as the degree of spontaneous relational alignment for the stimuli. We find that the degree of spontaneous alignment varies with the depth of matching relational structure and salience of local commonalities, as well as the relative positioning of the pictures.

The effects of relational depth and object richness are most clear in Experiment 3, where subjects presented with Sparse stimuli made more relational responses to Deep relations (M=0.54) and Medium relations (mean=0.42) than to Shallow relations (M=0.32). The results of Experiment 3 also suggest that salient local similarities can counteract a spontaneous preference for a relational match. More relational responses were made in the 1map condition to Sparse, High Systematicity items than other stimuli (M=0.54) in this study. However, few relational responses were made to Rich, High Systematicity items in the 1map condition (M=0.14).

An unexpected incidental result was that the way stimuli were presented also affected subjects' level of spontaneous relational mapping. Subjects made more relational responses in the 1map condition of Experiment 2 (mean=0.62 for Sparse stimuli only) than in Experiment 1 (mean=0.42) for the same stimulus set. The only difference between these studies was that in Experiment 1 the scenes were presented side-by-side, while in Experiment 2 they were presented one above the other. The event paths in these scenes moved from left to right or right to left. Thus, configuring scenes perpendicular to the direction of the event path may have made the alignment of the relational structures easier.

Subjects' tendency to make spontaneous relational mappings was affected by properties of the stimulus pairs, as well as by the way the stimuli were presented. This result is interesting in light of the suggestion that structural alignment is nearly intractable unless the goals for performing the comparison can constrain the process in some way (Holland, Holyoak, Nisbett and Thagard et al. 1986). In the one-shot mapping task, subjects' 'goal' is to find the best match for the cross-mapped object. There is nothing in the task itself that requires subjects to select the relational response. These findings suggest that pragmatic information is not a necessary component of structural alignment.

Additional Analyses

The following sections present further analyses that link these studies to previous work. In addition, secondary predictions of the structural alignment view are discussed. Readers who wish to skip these analyses should continue with the section on the implications of these studies for featural models.

Causal relations vs. perceptual relations. It has been suggested that perceptual and conceptual stimuli may be processed in a qualitatively different way (Torgerson, 1965). However, subjects in the similarity-first condition made more relational responses than subjects in the 1map condition in Experiments 1 and 2, with causal stimuli, and in Experiments 3 and 4, with perceptual stimuli. Thus, structural alignment appears to be a component of a general comparison process operating across a variety of stimulus types.

The Relational Shift Across Trials. Previous research has demonstrated that relations are often more heavily weighted in subjects' similarity judgments at the end of a series of relational trials than at the beginning (Goldstone, personal communication). A similar result was obtained here. Table 4 presents the proportion of relational responses in the first and second half of each study. In Experiments 1, 2 and 4 there was a clear tendency for subjects to make more relational responses in the first half than in the second, doing so in 10/12 conditions (83%). The data were less clear in Experiment 3, where subjects made more relational responses in the first half of the study than in the second on only 4/8 (50%) of the conditions. However, subjects in this study saw only six stimuli, and such a relational shift may occur after a larger number of trials. Overall, this analysis suggests that subjects were more influenced by relational commonalities later in the experiment than they were earlier.

Table 4
Mean Proporation of Relational Responses in First and Second Half of Experiments

	Mapping Condition					
	1map		Sim>1map		3map	
Experiment	First Half	Second Half	First Half	Second Half	First Half	Second Half
1	0.44	0.50	0.58	0.79*	0.52	0.69
2	0.54	0.65*	0.76	0.88	0.74	0.95*
3:L/S (a)	0.28	0.36	0.31	0.33	xx	xx
3:L/R	0.25	0.42	0.28	0.28	xx	xx
3:M/S	0.53	0.42	0.72	0.50*	xx	xx
3:M/R	0.31	0.50*	0.67	0.61	xx	xx
3:H/S	0.50	0.58	0.78	0.67	xx	xx
3:H/R	0.17	0.11	0.72	0.50	xx	xx
4:Sparse	0.05	0.09	0.53	0.64	0.41	0.53
4:Rich	0.30	0.20	0.27	0.25	0.38	0.49

Note: 'xx' denotes conditions not run.
(a) For Experiment 3: L/-Low, M/-Medium, and H/-High Systematicity, /S-Sparse and /R, Rich objects.
*$P < .05$, t-test, two-tailed

Although we are not committed to any particular explanation of the relational shift, an interesting explanation has been proposed by Kotovsky and Gentner (1990) for an observed relational shift in development. They hypothesized that carrying out a similarity comparison can change the way the stimuli are represented in the future. By their account, young children have an undifferentiated representation of dimensional relations like 'larger' and 'darker.' Through successive attempts to align 'larger' with 'darker,' the child comes to understand that both relations involve items that are 'greater' along some dimension. The general view that relational transfer can be promoted by analogical mapping has been proposed by other researchers as well (Gick and Holyoak, 1983, Hayes-Roth and McDermott, 1978, Kline, 1983, Skorstad, Gentner and Medin, 1988).

Extrapolating this explanation to the current experiments, it is possible that repeated viewings of similar relational structures over the course of an experiment can lead to a more differentiated relational structure. Eventually, this structure could be salient enough to serve as the basis for subjects' mappings. For example, subjects presented with a stimulus pair depicting monotonic increase in height might at first encode the stimuli by 'larger-than' relations between adjacent pairs. After noticing the similarity of the pairs, subjects might then encode future examples of monotonic increase by including information that the array is composed of objects increasing monotonically in height. This proposal is similar to one embodied in a connectionist model by Gasser and Smith (1991). Their model develops differentiated dimensional representations by performing a series of both implicit similarity comparisons (in the form of categorization tasks) and explicit similarity comparisons (where the network must judge a pair of stimuli as the same globally or along some dimension). The idea that multiple comparisons aids the development of uniform representations is compatible with the general structural alignment framework described here.

If the relational shift was the cause of the observed differences between mapping conditions, then it would have complicated interpretation of the experimental results. However, analysis of subjects' first two trials revealed the same pattern of responses as for all trials. The proportion of relational responses in the first two trials of each condition is presented in Table 5. When subjects made more responses in the similarity-first condition than in the 1map condition, they tended to do so in the first two trials as well. Similarly, in Experiments 3 and 4 when subjects made roughly the same number of relational responses in the similarity-first and 1map conditions, they did so in the first two trials as well. Thus, the cause of the relational shift appears to be different from the one responsible for the observed differences between conditions.

Relationship between rated similarity and relationality. Stimulus pairs with primarily relational commonalities are often judged to be more similar than stimulus pairs with primarily object commonalities (Rattermann and Gentner, 1987; Schumacher and Gentner, 1986; Goldstone, Medin and Gentner, 1991). For example, in a forced-choice task, Goldstone et al. (1991) found that subjects were much more likely to select a figure that was relationally similar to a target than a figure that had attribute similarities with a target when the two were placed in opposition. Of course, all such results depend on the specific levels of attributional and relational commonalities, so we cannot extrapolate too far. Still, it seems an important issue to investigate, so we approached this question with respect to our own data in two analyses.

Table 5
Proportion of Relational Responses in
the First Two Trials of all Conditions

	Mapping Condition		
Experiment	1map	Sim>1map	3map
1	0.25	0.42	0.38
2	0.44	0.60	0.60
3:L/S (a)	0.29	0.33	xx
3:L/R	0.21	0.33	xx
3:M/S	0.54	0.71	xx
3:M/R	0.29	0.67	xx
3:H/S	0.46	0.67	xx
3:H/R	0.17	0.75	xx
4:Sparse	0.13	0.38	0.31
4:Rich	0.38	0.19	0.31

Note: 'xx' denotes conditions not run.
(a) For Experiment 3: L/-Low, M/-Medium, and H/-High Systematicity, /S-Sparse and /R, Rich objects.

Table 6
Correlation between Mean Rated Similarity and Number of Relational Responses for All Conditions of All Experiments

		Mapping Condition		
Experiment	df	1map	Sim>map	3 map
1	6	-0.09	0.51	0.54
2	6	0.15	0.28	0.11
3:L/S (a)	4	0.31	-0.42	xx
3:L/R	4	-0.48	0.38	xx
3:M/S	4	0.33	0.31	xx
3:M/R	4	0.29	0.61	xx
3:H/S	4	0.29	0.30	xx
3:H/R	4	0.08	0.79*	xx
4:Sparse	14	-0.15	0.60*	0.46*
4:Rich	14	0.13	0.22	0.22

Note: 'xx' denotes conditions not run.
(a) For Experiment 3: L/-Low, M/-Medium and H/-High Systematicity, /S-Sparse and /R, Rich objects.
* $p<.05$, one-tailed

First, we calculated the correlation between the number of relational responses and the mean rated similarity of each item. On the basis of the prior research, we expected that similarity ratings would be positively correlated with the number relational responses given to an item. We anticipated that this finding would be most pronounced in the Sim->1map condition since it is there that subjects' similarity judgments should most influence the mapping task. The correlation between rated similarity and number of relational responses was calculated for all conditions in all experiments. These data are presented in Table 6. As expected, these correlations were positive in 19 of 23 conditions, although only 3 of 23 reached significance. Furthermore, as expected, all eight correlations in the Sim->1map condition are positive. The results of this analysis suggest that subjects gave higher similarity ratings to items when they placed the objects in correspondence based on the relations between them than when they mapped objects based on local similarities.

The relationship between similarity and relationality may be examined more directly by separating items given relational responses from items given object responses and finding the mean rated similarity given to the items in each group. This analysis, presented in Table 7, has the advantage that it is less sensitive than correlations to the small number of stimuli used in some of the studies. As anticipated, in 16/20 (80%) conditions, subjects gave higher mean similarity ratings to items to which they gave relational responses than to items to which they gave object responses.[12] These differences were statistically significant on six occasions. In the Sim->1map condition, higher similarity ratings were given to stimuli receiving relational mappings than to stimuli receiving object mappings in 8/9 (89%) of the experiments. Since previous studies have found that matching relational structures lead to high similarity judgments, the findings here strengthen our claim that subjects' one-shot mappings in the similarity-first condition reflect the preferred mappings from their similarity comparisons.

Level of similarity. Another question that can be asked about these data is whether subjects in one condition tended to find the stimuli more similar overall than subjects in another condition. These data are presented in Table 8. The mean rated similarity was highest in the 3map condition in all experiments where it was run. Furthermore, the mean rated similarity in the 1map condition was higher than that in the Sim->1map condition in 8/10 (80%) times. The structural alignment view does not make any predictions for differences in mean ratings across mapping conditions, but these data are not inconsistent with the general framework. Subjects in the 1map and 3map conditions (who had seen all of the pairs once before rating their similarity) may have given higher similarity ratings than subjects in the Similarity-first condition (who had not) because of their greater familiarity with the stimuli. The superiority of the 3map condition over the 1map condition may have arisen due to greater sensitivity to the matching relational structure. These data indicate that familiarity with the stimuli may be another factor that affects similarity judgments, and are consistent with the claim that differentiated relational structure may emerge with repeated exposures, as described above.

[12]There are 20 conditions reported in this analysis instead of 23, because the original data sheets for Experiment 2 were destroyed due to experimenter error.

Table 7
Mean Similarities Given Object Responses and Relational Responses

	Mapping Condition					
	1map		Sim>1map		3map	
Experiment	Object Response	Relational Response	Object Response	Relational Response	Object Response	Relational Response
1	5.13	4.98	3.90	5.15*	4.44	5.88*
3:L/S (a)	4.43	4.52	4.08	4.44	xx	xx
3:L/R	5.08	5.79	5.23	5.80	xx	xx
3:M/S	5.40	4.77	3.74	4.46	xx	xx
3:M/R	5.09	4.24	3.73	4.26	xx	xx
3:H/S	5.52	5.69	5.00	4.51	xx	xx
3:H/R	4.26	5.00	3.50	4.21*	xx	xx
4:Sparse	4.60	5.38	4.00	5.04*	4.89	6.09*
4:Rich	5.01	5.58	5.48	6.39	5.91	5.86

(a) For Experiment 3: L/-Low, M/-Medium and H/-High Systematicity,
/S-Sparse and /R, Rich objects.
* $p<.05$, Independent Samples t-test, one-tailed

One-to-one correspondence in the 3map control condition. The 3map condition was included in three of the four studies in order to demonstrate subjects' sensitivity to the matching relational structure. However, subjects' responses in this condition can also be used to make inferences about the performance of subjects in the one-shot mapping task. We examined all three mappings made by subjects in the 3map conditions of Experiment 4 to see if they satisfied the *one-to-one mapping* constraint. These studies in particular were analyzed because roughly the same number of object and relational responses were made. A one-to-one mapping was considered to be any pattern of responses where subjects placed each object in the top scene in correspondence with one and only one object in the bottom scene. This analysis revealed that, while subjects violated the one-to-one mapping constraint on 120/256 (40%) of their trials, subjects violated one-to-one mapping on only 4/140 (3%) trials on which subjects placed the cross-mapped objects in correspondence based on relational role. These results indirectly support the claim that subjects' relational responses in the one-shot mapping task reflect one-to-one mappings.

Table 8
Overall Similarities for all Stimuli
in all Experiments in all Conditions

	Mapping Condition		
Experiment	1map	Sim>1map	3map
1	5.08	4.76	5.31
2	5.86†	5.26	6.25*
3:L/S (a)	4.42	4.22	xx
3:L/R	5.34	5.39	xx
3:M/S	5.10†	4.19	xx
3:M/R	4.71†	4.07	xx
3:H/S	5.63†	4.65	xx
3:H/R	4.36	3.93	xx
4:Sparse	4.68	4.63	5.50*°
4:Rich	5.16	5.72	5.89°

Note: 'xx' denotes conditions not run.
(a) For Experiment 3: L/-Low, M/-Medium and H/-High Systematicity, /S-Sparse and /R, Rich objects.
*3map differs from Sim>1map, p<.05 (Bonferroni)
†1map differs from SIM>1map, p<.05 (Bonferoni)
°3map differs from 1map, p<.05 (Bonferoni)

Implications for Feature Independence

Previous work has relied heavily on direct measures of similarity through ratings and forced-choice tasks. While these measurements are straightforward and reliable, it is difficult to distinguish between competing models solely on the basis of subjects' feelings of similarity. It is often possible to recast one model of similarity in a manner that allows it to describe a pattern of similarity judgments taken as evidence supporting another.

For example, demonstrations that similarity comparisons are sensitive to relational commonalities in stimuli do not provide unambiguous evidence for the structural-alignment view of similarity over other models. For example, as we described above, Rattermann and Gentner (1987) provide evidence that subjects often found stories with primarily relational commonalities to be more similar than stories with primarily local commonalities. These data are consistent with the structural-alignment view of similarity, but they can also be handled by feature-matching models. If we were to assume that features are marked as providing local or global information, then more weight could be given to the global commonalities than to local ones.

It is more difficult to recast feature-matching models to explain Goldstone, Medin and Gentner's (1991) data collected in support of the MAX hypothesis. As in the explanation of the results of Rattermann and Gentner's study, we would have to assume that features are marked as providing local and global information. Then, local and global commonalities would

have to be placed in separate pools, and more weight would have to be given to the larger pool. By this explanation, the impact of a feature would not be independent of the effect of other features, but the components of similarity (i.e., (A∩B), (A-B) and (B-A) from Equation 1) would still be considered independent. From a processing perspective, the features would be placed in correspondence, and a separate evaluation process would determine whether there were more attribute similarities or more relational similarities. Elementary set operations would still determine the commonalities and differences of a pair, but feature independence would no longer be assumed.

The studies presented pose different problems for featural models. Cross-mappings rely crucially on the bindings between relations and their arguments. In order for a cross-mapping to exist at all, stimulus representations must be composed of both object information and relational information. Furthermore, the bindings of objects to relational structures must be clearly demarcated. Thus, in order to account for the present results, a feature-matching model would have to solve both the binding problem, and the attendant problem of how relational representations are compared.

As described above, a solution to the binding problem requires explicit links between relations and their arguments. While this problem could be addressed with configural features (Foss and Harwood, 1975), this solution would lead to a proliferation of features as every new relation would require a set of configural features to specify its bindings. Furthermore, commonalities between relations with different arguments would not be found, as the configural features would be specific to the particular relation they encode. The view presented here provides a more parsimonious solution to the binding problem by assuming stimuli are represented by combinations of attributes and relations. Pairs of propositional representations can be compared via the structural alignment process.

SME as a Process Model of Similarity Comparisons

We used SME (Falkenhainer, Forbus and Gentner, 1987, 1989) to simulate subjects' performance in the similarity-first condition. Many of the predictions derived from this model were borne out in the experiments. For example, in the first three studies, a high level of relational responding was observed in the Sim->1map condition when a good relational match existed. Furthermore, in Experiment 4, more relational responses were made to Sparse items than to Rich items, indicating that an object interpretation and a relational interpretation can compete. Finally, subjects were unlikely to make responses that were not based on object or relational commonalities.

In some respects, SME provides a better explanation for the data than other competing models of analogical mapping. For example, Holyoak and Thagard's (1989) ACME loosens the one-to-one mapping constraint so that it is only a pressure on alignment. For this reason, cross-mappings pose a particular difficulty for this model. When one-to-one mapping is not strictly enforced, salient relational structures will not lead the cross-mapped objects to be aligned on the basis of relational similarity. However, the data from these studies indicate that many relational responses were made following similarity comparisons, even in the presence of salient distinctive cross-mappings. Only when all objects could be place in correspondence based on local similarities (as in Experiment 4) were subjects affected by salient local matches.

The results of Experiment 4 are also at odds with predictions of Bakker and Halford's (1988) MATCHMAKER program. According to their model, when a relational match is made,

relational correspondences are determined first. Then the remaining objects are aligned based on local commonalities. However, subjects in Experiment 4 mapped on the basis of object similarities, even in the presence of a good relational match. Thus, it does not appear that object matches are calculated only after the relational correspondences are determined.

To the extent that SME is taken to be a process model for human similarity comparisons, the results obtained here also suggest some areas where the model should be modified. For example, early versions of SME generated all possible interpretations. Clearly, this approach is not psychologically plausible. Forbus and Oblinger (1990) developed an algorithm to allow SME to generate a single good matc' In addition, other process models of analogical mapping, like Holyoak and Thagard's (1989) ACME and Goldstone and Medin's (in press) SIAM, generate a single best interpretation. While this tack is more reasonable than an exhaustive search, the present data suggest that subjects consider both a local object match and a global relational match. Thus, more work must be done to determine how a small number of plausible interpretations can be generated. Furthermore, psychological research must concentrate on how many different interpretations actually compete during a similarity comparison.

In addition, the process that evaluates competing mappings needs to be studied in greater detail. Currently, SME makes use of Gentner's (1983) *systematicity principle*, by assuming that subjects prefer mappings that preserve deeply connected relational structures to interpretations that contain only scattered relational matches (Forbus and Gentner, 1990). Another possible evaluation heuristic can be derived from the results of Experiments 2 and 3, which suggest that the distinctiveness of a single cross-mapping does not affect subjects' relational alignment during a similarity comparison. One explanation for the relational advantage for these stimuli is that the relational match posits object correspondences for more objects than the object similarity match. By this interpretation, subjects may prefer global matches that allow them to place many objects in correspondence to those that place only a few object in correspondence. Currently, SME does not use this information, but the evaluation stage could be expanded to include it.

Another area where SME can be improved is in modeling the time course of analogical mapping. Studies by McKoon and Ratcliff (1990) suggest that information about object similarities is available before information about relational commonalities. This result is consistent with Goldstone's SIAM model (Goldstone, in preparation; Goldstone and Medin, in press), a connectionist system in which the number of processing cycles can be used to generate predictions about time. In that system, features are initially placed in correspondence based on local identities. Later in processing, features are more likely to be aligned when they are part of objects that have been placed in correspondence. Although SME does not currently have a mechanism for simulating the time at which competing mappings are available, a natural extension is to assume that matches become available when they posit object correspondences. By this suggestion, matches based on attributes and first-order relations (which take objects as arguments) would be available before matches based on higher-order relations (which take other relations as arguments). Further research must focus on this topic.

Finally, the output of SME is deterministic, while responses by subjects' are variable. The simplest explanation for this variability is that subjects vary in their encoding of the stimuli; one instance of this encoding variability is the apparent increase in the likelihood of representing the relations contained in the stimuli over the course of an experiment. Another possibility is that competing interpretations are given some probability of being used based on the evaluation

score they receive. A third possibility is that some resource, such as attention or effort, varies nondeterministically and affects the mapping outcome. For example, relational matches may be difficult to determine, and thus would be more likely to be calculated when attentional resources are high than when there is competition for attentional resources. Hofstadter and Mitchell (in preparation) have addressed variability in analogy directly. Their COPYCAT system searches for analogies using a *parallel terraced scan* which tries many possible matches simultaneously, searching each match at a depth roughly corresponding to its promise. Further research might examine the psychological plausibility of the parallel terraced scan.

Conclusions

The mechanism that determines psychological similarity is a natural and seemingly effortless process that can operate across a wide range of stimulus types. Among the variety of information used by alignment are object attributes, relations between objects, general domain theories and current context. This flexibility is both a blessing and a curse. On the positive side, similarity can be included as a basic component of a myriad of other cognitive processes. On the negative side, similarity becomes difficult to characterize (Medin, Goldstone and Gentner, in preparation), leaving some, like Nelson Goodman, to consider it "a pretender, an imposter, [and] a quack." (Goodman, 1972, p. 437).

While the structural alignment view of similarity may not reconcile all of the information thought to affect similarity, at least some of the seemingly inconsistent findings can be integrated into a single model. Our results indicate that similarity involves structural alignment. Objects are placed in correspondence based on matching relational structure when it is salient, though they can be aligned based on local similarities when the object commonalities are sufficiently salient. Thus, local and global information must be present in mental representations, and the process that compares these representations must take both into account. The structural alignment process we propose here provides a unified process model covering a wide range of phenomena involving local and global similarity processes, and offering a theoretical basis for examining different classes of similarity. While this work provides a hopeful start, we are still just beginning to describe similarity in its full complexity.

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